

**USING EMPIRICAL DATA TO FIND THE BEST MEASUREMENT FOR
TRAVEL TIME RELIABILITY**

A Thesis

by

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ABSTRACT

The value of travel time savings (VTTS) is often the largest benefit from transportation projects. As a result, the value of time (VOT) has been studied extensively. Recently, additional attention has been paid to the fact that travelers also benefit from reliable travel times. Thus, the value of reliability (VOR) is beginning to factor into cost/benefit analyses of transportation projects and understanding travelers' mode and route choices. VOR has almost always been estimated through stated preference data or survey based revealed preference data. In this research, empirical data was used in an attempt to estimate VOR.

The first concern regarding estimating VOR from empirical data is the lack of a definitive measurement for reliability. In this research, data from Katy Freeway, where travelers choose between tolled but reliable lanes and free but less reliable lanes, was used in an attempt to find the best measurement of reliability that could lead to the best explanation of travelers' lane choice. Multinomial logit models and mixed logit models were used to estimate travelers' lane choice based on trip attributes including travel time, travel time reliability and toll. Although models including only travel time and toll yielded reasonable results and VOTs (\$2.78/hr, \$9.09/hr, and \$10.52/hr for off-peak, shoulder, and peak-period travelers, respectively), adding alternative specific coefficient (ASC) or reliability measures to the models caused counter-intuitive results.

Although various reliability measures were used in the models, it was not possible to conclude which measure is the best as all models had counter-intuitive

results. Models also had a relatively large alternative specific coefficient which indicates a weak relationship between lane choice and other trip attributes. Therefore, the results from this research suggest that more research on how travelers perceive benefits of managed lanes (MLs) and choose between managed lanes and general purpose lanes (GPLs) is needed (particularly how, and if, they value reliability).

DEDICATION

To my dear parents, for their unlimited love and support

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TABLE OF CONTENTS

	Page
ABSTRACT	ii
DEDICATION	iv
ACKNOWLEDGEMENTS	v
TABLE OF CONTENTS	vi
LIST OF FIGURES	viii
LIST OF TABLES	ix
1. INTRODUCTION	1
1.1 Overview	1
1.2 Problem Statement	2
1.3 Research Objectives	4
1.4 Thesis Outline	4
2. LITERATURE REVIEW	6
2.1 The Value of Time	6
2.2 The Value of Travel Time	6
2.3 Value of Travel Time Reliability	8
2.3.1 Centrality-Dispersion	9
2.3.2 Scheduling Delays	9
2.3.3 Mean-Lateness	10
2.4 Stated Preference Studies	11
2.5 Revealed Preference Studies	14
2.6 Measurements of Travel Time Reliability	16
2.7 Summary of Literature Review	21
3. DATA	22
3.1 Katy Freeway	22
3.2 Datasets	25
3.2.1 Automatic Vehicle Identification Data	25
3.2.2 HCTRA Toll Data	27
3.2.3 Crash and Lane Closure Data	27
3.2.4 Weather Data	28

3.3 Data Process	28
3.3.1 Cleaning, Merging, and Randomization of Data.....	28
3.3.2 Trip Identification.....	29
3.3.3 Alternate Trip Generation	29
3.3.4 Lane Changes and the HOV Lane	31
3.3.5 Final Dataset.....	31
4. DATA ANALYSIS	34
4.1 Reliability Measures.....	36
4.2 Logit Models	40
4.3 Correlation between Travel Time and Reliability Measures	49
4.4 Discrete Choice Models for Travelers who Alternated their Lane Choice	51
4.5 The Influence of an Unacceptable Trip Experience.....	57
4.7 Unacceptable Last Trip Experience	61
4.8 One Trip for Each Traveler	64
4.9 Mixed Logit Models.....	70
4.10 Data Analysis Summary.....	78
5. CONCLUSION AND RECOMMENDATIONS.....	86
REFERENCES.....	90
APPENDIX	95

LIST OF FIGURES

	Page
Figure 1 Katy Freeway Map.....	24
Figure 2 Katy Freeway Sensor Location.....	26

LIST OF TABLES

	Page
Table 1 Toll Schedule on the Katy Managed Lanes (April 2012)	25
Table 2 Speed Comparison by Period	30
Table 3 Few Rows of the Trip Dataset.....	33
Table 4 Average Travel Time and Travel Time Standard Deviation by Period	34
Table 5 Average Travel Time and Travel Time Standard Deviation by Day	35
Table 6 Classification of Trips by Time of Day.....	36
Table 7 Reliability Measures.....	37
Table 8 Segments of Katy Freeway	39
Table 9 Average and Standard Deviation of Travel Time per Mile for Segments	40
Table 10 Logit Models Including Lane Closure and Rain Variables.....	42
Table 11 Logit Models with Time and Toll as Independent Variables.....	44
Table 12 Logit Models with the Standard Deviation (SD) as Reliability Measure	44
Table 13 Logit Models with the Coefficient of Variation (CV) as Reliability Measure	45
Table 14 Logit Models with the 95th Percentile as Reliability Measure	45
Table 15 Logit Models with the Interquartile Range (IR) as Reliability Measure	46
Table 16 Logit Models with the Shorten Right Range (SRR) as Reliability Measure	46
Table 17 Logit Models with the Travel Time Index (TTI) as Reliability Measure	47
Table 18 Logit Models with the Buffer Time Index (BTI) as Reliability Measure	47
Table 19 Logit Models with the Planning Time Index (PTI) as Reliability Measure.....	48
Table 20 Logit Models with the Misery Index (MI) as Reliability Measure	48
Table 21 Logit Models with the Percent of Unacceptable Trips (PT) as Reliability Measure	49
Table 22 Correlation between Time and Reliability Measures	51
Table 23 Logit Models with the Coefficient of Variation (CV) as Reliability Measure for Travelers Who Alternated Their Lane Choice.....	53

Table 24 Logit Models with the Travel Time Index (TTI) as Reliability Measure for Travelers Who Alternated Their Lane Choice	53
Table 25 Logit Models with the Buffer Time Index (BTI) as Reliability Measure for Travelers Who Alternated Their Lane Choice	54
Table 26 Logit Models with the Planning Time Index (PTI) as Reliability Measure for Travelers Who Alternated Their Lane Choice.....	54
Table 27 Logit Models with the Misery Index (MI) as Reliability Measure for Travelers Who Alternated Their Lane Choice	55
Table 28 Logit Models with the Percent of Unacceptable Trips (PT) as Reliability Measure for Travelers Who Alternated Their Lane Choice.....	55
Table 29 Logit Models with Time and Toll as Independent Variables for Travelers Who Alternated Their Lane Choice	57
Table 30 Classification of Trips by Travelers Who Alternated Their Lane Choice by Time of Day	57
Table 31 Logit Models with Bad Trip Experience (BTE) Indicator as the Measure of Reliability (Bad Trip Is a Trip Longer than 1.4 Times the Median Travel Time).....	60
Table 32 Logit Models with Bad Trip Experience (BTE) Indicator as Reliability Measure (Bad Trip Is a Trip Longer than 2 Times the Median Travel Time)	60
Table 33 Logit Models with Bad Trip Experience (BTE) Indicator as Reliability Measure (Bad Trip Is a Trip Longer than 80 th Percentile Travel Time)	61
Table 34 Logit Models with Last Trip Indicator (LTI) as Reliability Measure (Bad Trip Is a Trip Longer than 1.4 Times the Median Travel Time).....	63
Table 35 Logit Models with Last Trip Indicator (LTI) as Reliability Measure (Bad Trip Is a Trip Longer than 2 Times the Median Travel Time).....	63
Table 36 Logit Models with Last Trip Indicator (LTI) as Reliability Measure (Bad Trip Is a Trip Longer than 80 th Percentile Travel Time).....	64
Table 37 Logit Models for the Last Trip of Travelers with More than 5 Trips with Time and Toll as Independent Variables.....	67
Table 38 Logit Models for the Last Trip of Travelers with More than 5 Trips with the Coefficient of Variation (CV) as Reliability Measure	67
Table 39 Logit Models for the Last Trip of Travelers with More than 5 Trips with the Travel Time Index (TTI) as Reliability Measure	68

Table 40 Logit Models for the Last Trip of Travelers with More than 5 Trips with the Buffer Time Index (BTI) as Reliability Measure	68
Table 41 Logit Models for the Last Trip of Travelers with More than 5 Trips with the Planning Time Index (PTI) as Reliability Measure.....	69
Table 42 Logit Models for the Last Trip of Travelers with More than 5 Trips with the Misery Index (MI) as Reliability Measure	69
Table 43 Logit Models for the Last Trip of Travelers with More than 5 Trips with the Percent of Unacceptable Trips (PT) as Reliability Measure	70
Table 44 Mixed Logit Models with Time and Toll as Independent Variables	72
Table 45 Mixed Logit Models with the Coefficient of Variation (CV) as Reliability Measure	73
Table 46 Mixed Logit Models with Travel Time Index (TTI) as Reliability Measure....	74
Table 47 Mixed Logit Models with Buffer Time Index (BTI) as Reliability Measure....	75
Table 48 Mixed Logit Models with the Planning Time Index (PTI) as Reliability Measure	76
Table 49 Mixed Logit Models with the Misery Index (MI) as Reliability Measure.....	77
Table 50 Mixed Logit Models with the Percent of Unacceptable Trips (PT) as Reliability Measure	78
Table 51 VOT and VOR Obtained from Intuitive Logit Models.....	81
Table 52 Average Value of Reliability Offered by MLs in Peak Period	84

1. INTRODUCTION

1.1 Overview

Reliability of travel time can be used interchangeably with variability and can be referred to changes in travel time during a day or changes from day to day. Seven sources for variability in travel times have been identified: inadequate base capacity, demand fluctuations, traffic control devices, incidents, work zones, weather and special events (FHWA, 2005).

It is generally accepted that factors such as travel time, cost, comfort and safety influence the route choice of travelers. In addition to such factors, the reliability of travel time has also been found to be an important factor (Abdel-Aty et al., 1995; Bates et al., 2001; Lam and Small, 2001). Travel time reliability is more critical for trips with time constraints, such as trips to work, where delays and late arrivals may have serious consequences, but arriving early is undesirable.

Travel time reliability is a measure of consistency of travel time for a transportation service. The value of travel time reliability contributes to the value of a correct travel time estimation which is becoming more critical for travelers, shippers and transport agencies as traffic and congestion worsen. Reliable travel time helps travelers to better manage their schedules and is necessary for transport agencies to satisfy customers and remain competitive. When an element is important for the transportation systems' users, it must be important for transportation planners as well and should be considered during the transportation planning process. Not considering the benefit that

users gain from improved reliability might lead to significantly underestimating benefits from a transportation project. Moreover, when such an important factor is ignored, a complete understanding of travelers' behavior is not possible and this may lead to sub-optimal planning decisions.

1.2 Problem Statement

Due to fiscal constraints on transportation infrastructure expenditures, many agencies have found managed lanes (MLs) as a viable option that provides travel time savings and reliability to travelers with high values of time (VOT) and values of reliability (VOR). MLs provide travelers a tolled but guaranteed uncongested option while the general purpose lanes (GPLs) are free but might be congested. For those agencies that invest in MLs, it is important to predict how travelers choose between MLs and GPLs. This requires a good estimation of how travelers value the travel time and reliability offered by MLs. Although VOT has been studied comprehensively, studying VOR is relatively new and there are many uncertainties about it.

The first question about travel time reliability is how it should be measured. A reliability measure is needed to conduct a cost/benefit analysis or a before/after study for a project which may improve reliability. Furthermore, to understand how the travelers value reliability, it is first necessary to find out how they perceive reliability. In other words, discovering how travelers perceive travel time reliability is a prerequisite to finding how they value reliability, which is needed to explain and predict travelers' behavior.

Different measurements are suggested for travel time reliability including standard deviation, variance, 90th or 95th percentile, percent variation, misery index, buffer index, travel time index, planning time index, shorten right range, interquartile range, and frequency that congestion exceeds some expected threshold. In this thesis, revealed data from travelers on Katy Freeway, where travelers choose between MLs and GPLs, was used to find out which one of these measures most closely resembles how travelers perceive travel time reliability.

The dataset used in this research includes all travel information of those trips made on Katy Freeway by vehicles which have a transponder in April 2012. Therefore, the start time, travel time, travel length, cost (toll) and lane choice of each trip for a particular vehicle (known individually by transponder identifications) on Katy Freeway in April 2012 are available. This dataset was made from the raw dataset generated from automated vehicle identification (AVI) sensors which records the transponder ID and detection time of the vehicles. Transponder IDs were randomized for use in this analysis. Therefore, it is impossible to associate trips to a specific vehicle or person.

Travel time reliability for the MLs and GPLs of Katy Freeway were calculated using different measurements of reliability. Discrete choice models were developed using each measurement and other trip attributes such as travel time and toll. The best measurements of reliability are those included in the best model that explains travelers' behavior. As the final step, VOT and VOR were estimated.

1.3 Research Objectives

The objective of this research is to discover how travelers perceive reliability of travel time using empirical data. Travelers' perception and value of reliability is important as it may influence their travel choices. As a factor that impacts travelers' behavior, travel time reliability must be well understood by planners and be considered during the decision making process.

1.4 Thesis Outline

This thesis is organized as follows:

- Section 1 includes an introduction to the research problem.
- Section 2 includes a review of the available literature on travel time reliability. This section also includes an introduction to value of travel time. Section 2 continues with a discussion about methodologies used to estimate value of travel time reliability. The reliability measures that were used in different studies are also discussed. The findings and uncertainties in the reviewed literature are then summarized.
- Section 3 focuses on datasets. Details about all datasets used in this thesis are provided, including Automatic vehicle identification (AVI) sensors, toll schedule, raw data set generated by AVI, weather data and lane closure data. The methods used to merge and process these data are also explained.
- Section 4 includes models developed for different times of day using different measures of reliability. It focuses on analyzing the coefficients of attributes in models and the relative importance of each attribute in lane

choice. The section continues with finding the quantitative value of travel time and travel time reliability using these coefficients of the attributes.

Difficulties, limitations and assumptions in modeling process and their possible impacts on the results are then discussed.

- Section 5 contains conclusions from this thesis along with recommendations and suggestions for future research.

2. LITERATURE REVIEW

There is no doubt that travel time and travel time reliability can influence a traveler's route choice. In this section of this thesis, the available literature regarding how travelers perceive and value travel time and travel time reliability is examined with the goal of determining what has been proven as well as identifying remaining uncertainties regarding these two factors.

2.1 The Value of Time

In the early stages of studying the value of time, it was linked to a labor supply demand system where time is a finite element which can be used either for work or leisure. This led to the idea to value time the same as opportunity cost (forgone wage) or in other words, value time equal to wage rate (Concas and Kolpakov, 2009). DeSerpa (1971) recognized that the time required for any activity has two distinct parts: one part is necessary (minimum amount of time) and one part can be a matter of choice. This led to a new term: value of time saving. Most initial studies identified a range for the value of time with zero at minimum and wage rate as the maximum (Shaw, 1992). However, later research indicated that value of time can be much higher than someone's wage rate (Concas and Kolpakov, 2009).

2.2 The Value of Travel Time

The value of travel time can be defined as the amount of money a traveler is willing to pay to reduce his or her travel time. There are three main reasons for studying the value of travel time: (1) it is important in the transportation planning and decision

making process, (2) it helps to understand travelers' behavior, and (3) it is a necessary input for a good travel demand model (Small, 2012). Due to its importance, there are literally hundreds of studies on this topic (Wardman, 1998). The most common way to investigate the value of travel time is using stated preference or revealed preference data to develop mode choice models and compare the marginal rates of substitution between the cost and travel time of the alternative modes. However, other approaches such as examining residential housing costs (it is assumed that people will pay more for a house that reduces their travel costs) are also available (Small et al., 1999).

Beesley (1965) was one of the first researchers who used the mode choice approach; he estimated value of travel time to be 31 percent and 49 percent of the wage rate for a low income group and a high income group, respectively. O'Farrell and Markham (1975) estimated value of in-vehicle travel time and out-of-vehicle travel time to be 86 and 189 percent of the wage rate, respectively. There are several similar studies which offer a wide range for the value of travel time. Cherlow (1981) reviewed many of these studies and concluded that there is no single value of travel time applicable to all people in all circumstances. Recently, Perk et al. (2011) studied the value of time for I-95 travelers in Miami, they found it to be approximately 49 percent of the hourly wage rate ranging from \$2.27 per hour to \$79.32 per hour with a mean of \$32.00 per hour. In another study, Burris and Xu (2006) found the value of travel time to be approximately 45 percent of hourly wage rate for Houston ML travelers. Overall, recent studies mostly value travel time in the range of 20 percent to 50 percent of a traveler's hourly wage rate (Concas and Kolpakov, 2009).

Patil et al. (2011) investigated the value of travel time for travelers on MLs in seven different situations, including one normal situation and six urgent situations. They found that in an urgent situation travelers' value of time is drastically higher than a normal situation. They concluded that, the benefit from MLs would be underestimated if the time saved using MLs for urgent trips is valued the same as time saved for normal trips.

2.3 Value of Travel Time Reliability

In a road trip, travel time can consist of two parts: free flow time when there is no (or very little) traffic and additional time due to lowered speed resulting from traffic congestion (Carrion and Levinson, 2012). The additional travel time can be considered travel time variation. Wong and Sussman (1973) suggested three components for variations: (1) predictable variation resulting from differences between winter and summer, days of weeks, peak hour and off peak, (2) irregular variation resulting from changes in network conditions because of an incident and (3) random variations attributed to each traveler.

Travelers may perform some adjustments to offset the added cost of predictable variations such as changing their departure time, route or mode of travel. Therefore, the unpredictable variation is particularly troublesome for travelers. Travel time reliability is directly linked to unpredictable variations: high travel time variability means high travel time unreliability. Three frameworks have been developed to understand the travel time reliability: (1) centrality-dispersion (commonly known as mean-variance), (2) scheduling delays and (3) mean-lateness. These three approaches are described below.

2.3.1 Centrality-Dispersion

This framework was introduced by Jackson and Jucker (1982). This is based on the concept that travelers want to minimize disutility from travel time and travel time unreliability; and can be formulated as shown in Equation 1:

$$\text{Minimize } \mu(T_p) + \lambda_k \sigma(T_p), p \in P_{AB} \quad (1)$$

In above formulation $\mu(T_p)$ and $\sigma(T_p)$ are the mean and standard deviation of the travel time distribution for each route (p) in the available choice set between an origin destination pair (AB). λ_k shows the degree to which the variance of travel time is undesirable to traveler k. This model is usually estimated using discrete choice methods. Adding a travel cost variable (C_p) to this utility form (see Equation 2), the value of time and value of travel time reliability can be estimated using the marginal rate of substitution:

$$U(p) = \lambda_{1k} \mu_{Tp} + \lambda_{2k} \sigma_{Tp} + \lambda_{3k} C_p \quad (2)$$

$$VOT = \frac{\partial U / \partial \mu_T}{\partial U / \partial C} = \frac{\lambda_{1k}}{\lambda_{3k}} \quad (3)$$

$$VOR = \frac{\partial U / \partial \sigma_T}{\partial U / \partial C} = \frac{\lambda_{2k}}{\lambda_{3k}} \quad (4)$$

2.3.2 Scheduling Delays

This approach is linked to departure time choice which is based on the time constraint and the cost associated with arriving early or late. Small (1982) developed a utility maximization based model where travelers' utility is influenced by departure time and workplace constraints.

$$U(t_d)=\beta_1 T+\beta_2 SDE+\beta_3 SDL+\beta_4 DL \quad (5)$$

Equation 5 shows the utility function for departure time (t_d). As can be seen, travel time (T), schedule delay early (SDE , defined as $\text{Max}(0, SD)$), schedule delay late (SDL , defined as $\text{Max}(0, SD)$) and a dummy variable (DL) which equals to one when it is a late arrival ($SDL > 0$) are included in the utility function. The SDE , SDL and DL , each represent considerations for workplace constraints. By adding a travel cost variable to this utility form, value of time, value of scheduling delay early ($VSDE$), and value of scheduling delay late ($VSDL$), can be estimated using marginal rate of substitution:

$$VOT = \frac{\partial U / \partial T}{\partial U / \partial C} \quad (6)$$

$$VSDE = \frac{\partial U / \partial SDE}{\partial U / \partial C} \quad (7)$$

$$VSDL = \frac{\partial U / \partial SDL}{\partial U / \partial C} \quad (8)$$

2.3.3 Mean-Lateness

This approach was first introduced by Association of Train Operating Companies (ATOC) and has become the standard for analysis of reliability of rail in the UK. In this approach, the utility function consists of two elements: schedule journey time ($SchedT$) and mean lateness (L) at destination (see Equation 9).

$$U = \beta_1 SchedT + \beta_2 L^+ \quad (9)$$

Lateness is defined as the time between scheduled arrival and actual arrival; however, negative values meaning early arrivals are not considered. As with the two

other approaches, by adding a travel cost variable to this utility form, value of lateness (VOL) can be estimated (see Equation 10) (Batley and Ibáñez, 2009).

$$VOL = \frac{\partial U / \partial L}{\partial U / \partial C} \quad (10)$$

Among the three frameworks, centrality-dispersion has been the predominant approach for the analysis of reliability as scheduling models require data on travelers' arrival time and usually rely on simulation procedures. In this research, centrality-dispersion framework was used, which means that travel time, a measure of reliability and cost of travel were included in the utility functions. The only difference is that the actual travel time for each trip was used instead of the mean travel time because data for travel time for each trip was available. Since travel time information is provided to the public through media reports, displays on roadside electronic message signs, and the Houston TranStar website, it is reasonable to assume that travelers have a good estimation of travel times on both lanes.

As mentioned, estimates of value of travel time reliability have been obtained mostly using discrete choice models. Data for developing these kinds of models can be stated preference data or revealed preference data.

2.4 Stated Preference Studies

Most research has used stated preference techniques to find the value of travel time reliability. This method has proven to be more useful than revealed preference studies as revealed data usually cannot provide the required level of detail (Bates et al., 2001). In early studies, it was common to ask respondents about their choice regarding

pairs of hypothetical routes, where the route with shorter mean travel time had possible delays (Jackson and Jucker, 1982; Abdel-Aty et al., 1995).

Black and Towriss (1993) used a more detailed approach; they conducted interviews via a mail-back survey to gather the required data. Survey respondents were asked to choose between different options with a varying spread of travel times, mean travel times, and travel costs. They verified that travel time reliability (measured as standard deviation of travel time) is a significant factor, although it was found to be valued at only 55% of the value of mean travel time. They also defined the term of reliability ratio as the value of reliability over value of time (Equation 11). This term helps to understand how travelers are likely to respond to changes in reliability relative to changes in mean travel time.

$$RR = \frac{VOR}{VTT} \quad (11)$$

Small et al. (1999) also used mail back surveys to gather data. Respondents were asked to choose between two alternative choices with mean travel times, a distribution of five arrival times (with a preferred arrival time), and a travel cost. They used mean-variance models, scheduling models and combined models, with data on monetary cost trade-offs, to estimate value of travel time reliability. They found the reliability ratio to be 3.22, which was substantially higher than what Black and Towriss (1993) found.

Travel time reliability by nature is difficult to present without using statistical terms. Therefore, survey design and the way that questions are presented could impact the estimation of value of travel time reliability. As a result, in late 1990s and 2000s,

attempts to improve the design of questions about reliability were undertaken. Bates et al. (2001) used a new design to present variability. They put possible arrival times in boxes (i.e. each time in one box) and put the boxes in a circular arrangement.

Hensher (2001) used bar diagrams to present the alternatives and divided their total travel time into free flow, slowed down, stop/start, and uncertainty. A cost was also assigned to each alternative to be able to extract the trade-off between cost and value of each component of time. As the uncertainty component used in his study does not include measures of reliability (e.g. variance), it could be mostly related to the schedule delay approach. Hollander (2006) used five bars per alternative in his survey, time of departure and arrival were indicated at top and bottom of the bar, respectively. He estimated a mean variance model which indicated the reliability ratio to be 0.1 and quite low compared to results from other studies.

Tseng et al. (2009) used face-to-face interviews to find out how different types of questionnaires were understood. They found that verbal description (e.g. Small's format) was preferred and understood by most of respondents, while Bates et al.'s format was not preferred. They also recommended not using Hollander's format of variability presentation.

Devarasetty et al. (2012) conducted a survey to better understand the value of travel time and value of travel time reliability. They used a picture format survey for half of their respondents and a text format survey for the other half of their respondents. It was found that both formats were similarly understood as the respondents' choices were similar. They used coefficient of variability as the measure of reliability; and found

value of travel time and value of travel time reliability to be \$22/hr and \$28/hr, respectively.

Concas and Kolpakov (2009) reviewed the literature on value of travel time reliability and recommended that the reliability ratio be estimated at 0.8 to 1 under ordinary circumstances. However, under non-flexible arrival constraints it could be up to 3.

2.5 Revealed Preference Studies

So far, there have been few studies that have used revealed preference data to estimate a value of travel time reliability. The reason could be the scarcity of alternative routes with different travel time reliability and difficulties in gathering travel time data. There are two types of revealed preference studies that are distinct by the way that travel time is measured: objective travel time distribution, where travel time is measured by devices such as loop detectors, and subjective travel time distribution, where travel time is reported by travelers.

Lam and Small (2001) used data from California State Route 91 (SR-91), which includes four free lanes and two high occupancy toll (HOT) lanes, to estimate travelers' value of travel time reliability. They collected revealed preference data through mail surveys plus travel time data was collected through loop detectors. Travel times from loop detectors were not necessarily the respondents' trips' travel time. Moreover, the loop detector data were from one year prior to the survey: they used a coefficient to increase travel time to account for the growth in congestion. They used two measures for centrality (mean and median) and two measures for variability (standard deviation and

90th percentile minus median). In their best model, median and difference between the 90th percentile and the median were used as measures of travel time and reliability, respectively. They found the value of travel time reliability to be \$15.12/hr for men and \$31.91/hr for women, which were 48% and 101% of the average wage rate in their sample.

Small et al. (2005) used revealed preference data (collected through phone interviews and a mail survey) and stated preference data (collected through a mail survey) to investigate the value of travel time reliability. The respondents were the travelers on SR-91 where the alternatives were HOT lanes and GPLs. Travel time data were obtained through field measurements during similar time periods as the subjects were traveling. They used the difference between 80th and 50th percentile travel time to measure travel time reliability as they found it to fit the model better than alternate measures such as standard deviation; and used mixed logit to develop lane choice model. The value of travel time reliability was found to be \$19.56/hr (85% of the average wage rate) and its heterogeneity was found to be significant.

In the two studies above, the travel time was not what respondents actually experienced. However, travel time used in the Small et al. (2005) study is closer to the actual travel time. To overcome this issue, Carrion and Levinson (2013) used a different approach and designed a GPS-based study. They studied Interstate 394 corridor lanes in Minneapolis, Minnesota. In their study, 18 commuters were recruited and equipped with GPS devices and instructed to commute for two weeks on each of the three alternatives: I-394 HOT lanes, I-394 GPLs, and a signalized arterial close to the I-394 corridor. Then,

travelers were asked to drive on their preferred route. The revealed data were used to develop discrete choice models to find the value of travel time reliability. They used three different measures for reliability: standard deviation, shorten right range (90th percentile minus median), and interquartile range (75th percentile minus 25th percentile). Although their estimates of the value of time and value of reliability were low (about \$8/hr), the estimated confidence interval was wide and included some estimates from previous studies. The main drawback of this approach is the small sample size as a larger sample size would be too costly.

2.6 Measurements of Travel Time Reliability

Differences in the research approaches to estimating a value of travel time reliability are a key obstacle in comparing the results from these studies. These differences can be categorized as follows:

- Data type (revealed preference, stated preference);
- Scheduling versus reliability measures;
- Various travel time reliability measures;
- Travel time unit;
- Presence of heterogeneity (observed and unobserved);
- Choice dimensions (mode, route and etc.)

Using different measures of reliability would lead to variation in results.

However, there is one thing that all measures have in common; they all relate to the shape of travel time distribution. The wider travel time distribution means more variable or unreliable travel time.

There are statistical measures such as standard deviation and coefficient of variation which can be used as a measure of reliability. Standard deviation measures the extent of dispersion of travel time around the mean travel time. The coefficient of variation (CV) or percent variation is defined as the ratio of standard deviation (SD) to the mean (μ) and provides normalized measure of dispersion.

$$SD = \sqrt{\frac{1}{N} \sum_{i=1}^N (x_i - \mu)^2} \quad (12)$$

$$CV = \frac{SD}{\mu} \quad (13)$$

A higher CV value shows higher unreliability. However, these measures may not be particularly accurate when the distribution of travel time is skewed. It happens when some travel time oddly differ from the mean value. One way to capture this is using a range of travel times, from the median to the extreme values (Tilahun and Levinson, 2010). However, using the right range as a measure of variability implies that travelers are solely concerned about lateness (Carrion and Levinson, 2013).

$$\text{Right range: longest travel time} - \text{median travel time} \quad (14)$$

To consider high values, but also avoid measurement errors, the shorten right range can be used as a measure of variability (see Equation 15).

$$\text{Shorten right range: } T_{90} - T_{50} \quad (15)$$

Where:

T_{90} = 90th percentile travel time

T_{50} = 50th percentile travel time

Small et al. (2005) used the difference between 80th percentile and 50th percentile instead of the shorten right range as data was too sparse to have a definitive 90th percentile. Interquartile range of travel time distribution is another range used to measure reliability (see Equation 16). Extreme travel times are disregarded in this measure and the focus is on overall travel time variability.

$$\text{Interquartile range: } T_{75} - T_{25} \quad (16)$$

Where:

T_{75} = 75th percentile travel time

T_{25} = 25th percentile travel time

There are other travel time reliability measures which are assumed to be closer to traveler's perception of travel time and are defined as buffer-time measures (Lomax et al., 2003). These measures are also recommended by FHWA and are listed below:

$$\text{Planning time index} = \frac{T_{95}}{FFTT} \quad (17)$$

$$\text{Buffer time index} = \frac{T_{95} - ATT}{ATT} \quad (18)$$

Where:

T_{95} = 95th percentile travel time

FFTT= Free flow travel time

ATT = Average travel time

The above indexes are illustrated by the following examples. A planning index of 2 means that for a 5-minute trip in free-flow traffic, the travelers should plan for a 10-minute trip so that they can arrive on time 95 percent of the time. A buffer index of 20%

means that travelers need to plan for the trip to be 20% longer than average to arrive on time 95 percent of the time.

Tardy trip indicators use a specific threshold of unacceptable late arrival time and indicate the amount of unacceptably late trips (Lomax et al., 2003). Two of these indicators are shown in Equations 19 and 20.

$$\text{Percent of unacceptable trips} = \left(\begin{array}{l} \text{percent of trips with travel time} \\ \text{greater than a specific threshold} \end{array} \right) \quad (19)$$

$$\text{Misery index} = \frac{\left(\begin{array}{l} \text{Average travel time for} \\ \text{the longest 20\% of trips} \end{array} \right) - ATT}{ATT} \quad (20)$$

In Equation 19, the percent of unacceptable trips can be the percent of trips with travel time greater than the median travel time plus a percent of the median travel time. Haliburton (2002) recommended travel time greater than the median travel time plus 10 percent of the median to be unacceptable travel time. The other tardy trip indicator, the misery index, measures the average number of minutes that the worst trips exceed the average travel time. It should be noted that the exact percentage of the “worst trips” used for calculating the misery index does not have to be 20 percent. It can be adjusted to meet the needs of analysis.

van Lint and van Zuylen (2008) showed that results from using standard deviation, coefficient of variation, buffer time index and misery index are significantly different which verifies that using different measures of reliability would lead to different results. They introduced three new measures: skew, width of travel time and a function of both width and skew (see Equations 21, 22 and 23). They stated that travel

time distribution is only symmetric in case of free flow condition and is mostly skewed; therefore, width and the skew of the travel time distribution are more robust measures of reliability.

$$\lambda^{skew} = \frac{T_{90} - T_{50}}{T_{50} - T_{10}} \quad (21)$$

$$\lambda^{width} = \frac{T_{90} - T_{10}}{T_{50}} \quad (22)$$

$$UI_r = \begin{cases} \frac{\lambda^{width} \ln(\lambda^{skew})}{L_r} & \lambda^{skew} > 1 \\ \frac{\lambda^{width}}{L_r} & \text{Otherwise} \end{cases} \quad (23)$$

T_{10} also denotes 10th percentile travel time and L_r is the route length. The skew defined in their study is different from the well-known equation for skew-ness which is shown in Equation 24. For all three indicators the high values show high travel time unreliability. These measures can be used to compare reliability of different routes as they are relative ratios. However, due to the difficulty for a non-technical person to understand these measures, they are not widely used (Concas and Kolpakov, 2009).

$$\text{Skewness} = \frac{\frac{1}{n} \sum_{i=1}^n (x_i - \mu)^3}{\left(\frac{1}{n} \sum_{i=1}^n (x_i - \mu)^2\right)^{3/2}} \quad (24)$$

There are also probabilistic approaches to measure travel time reliability. In this approach, reliability is defined as the probability that a trip can be made successfully within a specific interval (Asakura, 1999; Chen et al., 2002). The main disadvantage of defining travel time reliability as a probability density function is having a parameterized measure which does not allow monetizing the value of reliability.

In addition to the above reliability measures, this research introduced new variables. These new variables are not common measures of reliability but might be close to travelers' perception of reliability. A variable which indicates whether a traveler's last trip on a lane set was unacceptable and a variable which shows whether a traveler had any unacceptable trip on a lane set in his/her previous trips were introduced and included in the discrete choice models.

2.7 Summary of Literature Review

In most of the reviewed studies, two or three reliability measures were compared to choose the best one. However, due to a lack of real world data on travel time and travel time reliability, all the measures were not compared to find the closest one to travelers' perception of reliability. On the other hand, studies have shown that different reliability measures would lead to different results. Therefore, a more comprehensive study that compares different reliability measures is needed.

3. DATA

In this section of the thesis, details about all datasets used in this thesis including toll schedule, raw data set generated by automatic vehicle identification (AVI) sensors, toll data, weather data and lane closure data are provided. The way that these data were merged and processed are also explained.

3.1 Katy Freeway

Katy Freeway connects the city of Katy to the city of Houston and was constructed in the 1960s. At that time it had only six to eight lanes. However, population growth in West Houston has caused substantial traffic congestion on the freeway. In 2000, traffic was very congested, prompting TxDOT to upgrade the Katy Freeway. In 2002, the old railway close to the freeway was bulldozed to clear the area for upgrading a 12-mile section of the freeway between SH6 and the I-10/I-610 interchange. In 2004, construction began on the freeway. The 12 mile section was widened, with up to six GPLs in each direction. Additionally, two variably priced MLs for each direction were added in the middle of the highway. MLs have been fully operating since April 2009; and are maintained by the Harris County Toll Road Authority (HCTRA). Figure 1 shows a map of Katy Freeway. MLs can be seen in the middle with four entry and exit points in both directions.

Katy Freeway MLs provide travelers with a new commuting option, which generally requires less travel time and is more reliable, in return for paying a toll. As shown in Figure 1, Katy Freeway has three toll plazas (near the cross streets of Eldridge, Wilcrest, and Wirt). Tolls are collected electronically at the toll plazas. Vehicles need to have a transponder to be charged a toll and be able to use the MLs. High occupancy vehicles (HOVs) with two or more occupants and motorcycles can use MLs for free during HOV-free hours, Monday through Friday 5 a.m. to 11 a.m. and 2 p.m. to 8 p.m. This discount is provided as an incentive to encourage carpooling. However, HOVs and motorcycles have to pay the same toll as single occupancy vehicles (SOVs) at all other times. In order to avoid the toll during the HOV-free hours, HOVs and motorcycles need to make sure to pass the toll plazas in the HOV lane, the leftmost lane of MLs. Toll rates vary by the time of day. Table 1 shows the toll schedule during April 2012 which is the analysis period for this research.

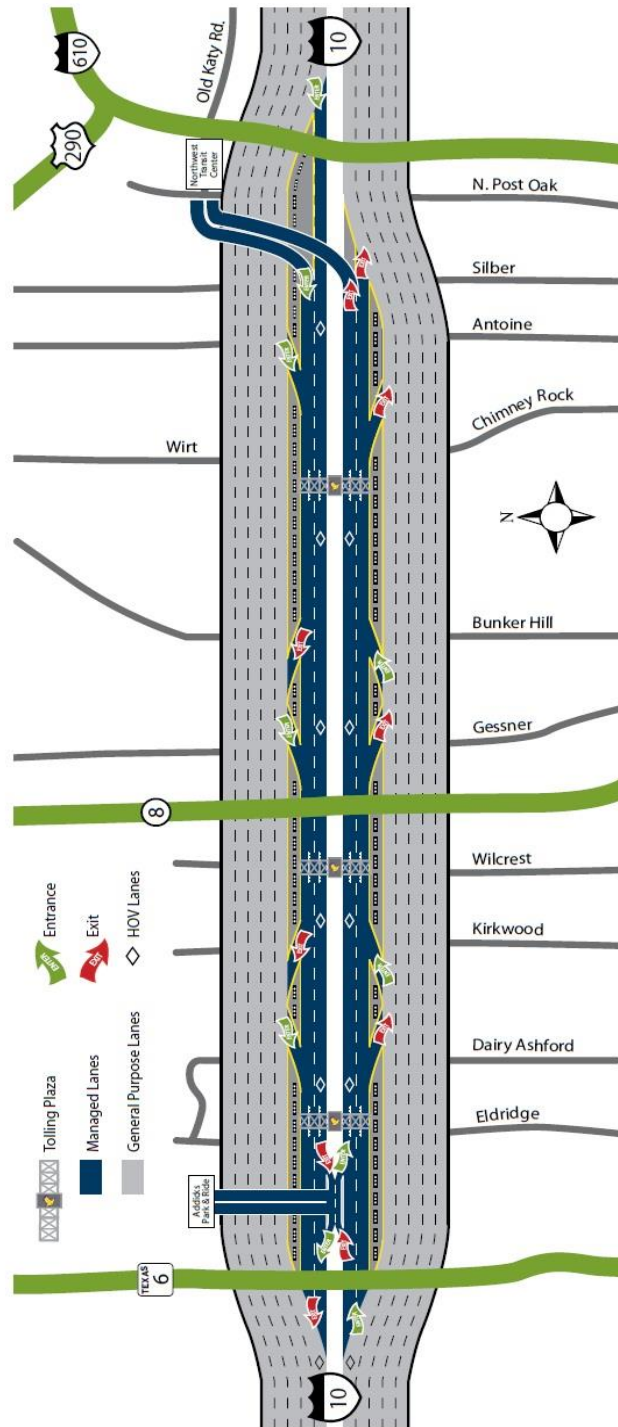


Figure 1 Katy Freeway Map
 Source: Harris County Toll Road Authority

Table 1 Toll Schedule on the Katy Managed Lanes (April 2012)

Time Period	Toll Plaza		
	At Wilcrest	At Wirt	At Eldridge
Peak Period (7–9 a.m. Eastbound and 4–6 p.m. Westbound)	\$1.20	\$1.20	\$1.60
Shoulder (6–7 a.m. and 9–10 a.m. Eastbound and 3–4 p.m. and 6–7 p.m. Westbound)	\$0.60	\$0.60	\$0.80
Off-Peak Period (All Other Times)	\$0.30	\$0.60	\$0.40

Source: Harris County Toll Road Authority

3.2 Datasets

Automatic vehicle identification data, toll data, lane closure and weather data were used in this research. Each of these datasets are described below.

3.2.1 Automatic Vehicle Identification Data

Texas Department of Transportation (TxDOT) operates automatic vehicle identification (AVI) sensors both on MLs and GPLs along the Katy Freeway. Figure 2 shows the location of the sensors, each number indicates a specific sensor. These sensors detect vehicles with transponders and record the transponder ID of the vehicle and time of detection. The AVI data, which was obtained from TxDOT, contains all sensor detection records for 2012. This dataset was used to identify the trips on the MLs and GPLs. In 2012, 225,118,768 records for 1,933,347 unique transponder IDs were obtained by these 38 TxDOT AVI sensors on Katy freeway. Due to inevitable problems regarding working with a huge dataset, only records from April were used in this

research. For April, 870,819 unique transponder IDs with 4,496,918 trips were identified. Transponder IDs were randomized for use in this analysis. Therefore, it is impossible to associate trips to the actual vehicle or the person who made the trips.

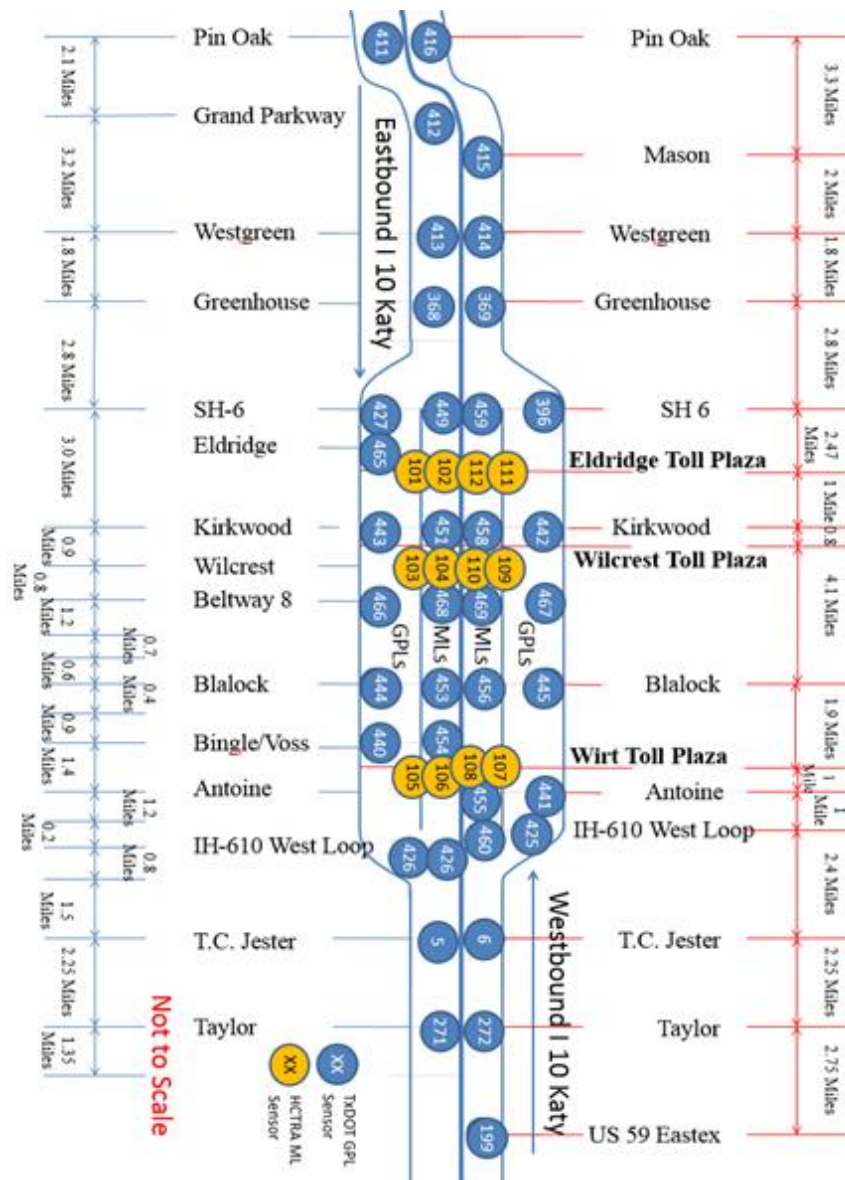


Figure 2 Katy Freeway Sensor Location

3.2.2 HCTRA Toll Data

The HCTRA dataset contains records of all vehicles with transponders that passed toll plazas on the MLs on the Katy Freeway. Each record includes the time of detection, transponder ID of the vehicle, location, toll plaza ID number, and lane number. This dataset was used to supplement AVI data to better identify trips along the MLs, assign the correct toll to each trip and also better identify free trips during HOV-free hours. Since transponder IDs were randomized, it is impossible to associate trips to actual vehicle or the person who made the trips. This dataset includes 14,769,730 records for 2012 and 1,310,043 for April.

3.2.3 Crash and Lane Closure Data

A dataset containing all information about all incidents and lane closures on Katy Freeway for 2012 was obtained from TxDOT. This dataset was used to see how lane closures may impact decision making of the traveler. In theory, the way that incidents influence lane travelers' lane choice is through impacting travel time and travel time reliability. Therefore, the impact of crashes was already accounted by measuring travel time and travel time reliability. However, as lane closures are announced through the radio, they may have impacted travelers' decisions in other ways, so lane closures were also included as independent variables. The type of incident, type of closed lanes (ML, GPL, or frontage), number of closed lanes, duration for lane closure, and location of the incident were included in the dataset. For April, 121 incidents were recorded and were included in the analyses. In this research, it was assumed that only trips starting at a location upstream of the incident were impacted by the incident.

3.2.4 Weather Data

Weather data includes hourly rainfall in inches near the Katy Freeway. The dataset was obtained from the National Climatic Data Center. A variable which indicates heavy rain (rainfall greater than 0.4 inches in an hour) was added to the trip dataset. In April 2012, there were four hours with more than 0.4 inches of precipitation.

3.3 Data Process

The above datasets were processed by Santosh Rao Danda, one of Professor Burris's students, to identify trips and trip attributes. The procedure used to identify the trips is briefly explained below.

3.3.1 Cleaning, Merging, and Randomization of Data

As a first step, duplicate or incomplete information from AVI and HCTRA data were removed. Toll data was merged with the AVI sensor data. In order to enable the merge, each toll booth was assigned a sensor number, instead of the plaza ID, to match the AVI sensor data. Unnecessary attributes were deleted. The new merged dataset includes the time stamp, sensor number, and transponder ID. To make sure that no transponder owner could be identified using transponder IDs, each transponder ID was assigned to a unique random ID, and the original transponder IDs were deleted. Data for random IDs that were detected only once (at a single location) were deleted as a vehicle needs to be identified at least at two locations to have a trip. After these initial steps, the total number of records (individual transponder reads at a specific sensor) for April was 19,383,952.

3.3.2 Trip Identification

Records were sorted by random ID. Therefore, all detections for a specific random ID were placed consecutively to be able to trace a trip through the freeway. For example, a specific random ID identified at sensors 445, then 442, then 369, and finally 414 within a given time period was converted into a single trip entering the freeway at reader 445 and exiting at reader 414 (refer to Figure 2). The time difference between two consecutive detections for the same random ID had to be less than 10 minutes to assume that the two detections were part of a single trip. Using the time and location of the first and last detections, travel times and distance of the trips were calculated. Based on the time of detection, the ML the vehicle was in, and the toll schedule, tolls were assigned to the trips that were detected at toll plazas. The total toll for the trips was equal to the sum of tolls paid along the trip at up to three different toll booths.

3.3.3 Alternate Trip Generation

To develop logit models and understand how travelers choose between MLs and GPLs, it would be necessary to model the choice the traveler was making. Therefore, for each trip on the MLs, the attributes of a similar trip on GPLs was needed, and vice versa. Therefore, for each trip, an alternate trip was created for the lane set that was not chosen.

Alternate trips have the same start time and pass through the same section of the freeway but on the other set of lanes. For trips on the toll lane the alternate trip is free on GPLs. For trips on the GPLs there would be a tolled trip created. The toll depends on the number of toll booths in the section of the freeway on which trip was made and the time of day (see Table 1).

For the alternate trip, the travel time was calculated by taking the average of travel times on the same section of the freeway on the alternative lane (lane that was not chosen) during the same 15-minute interval in which the trip was made (same 15 minute interval on the same day). Average speeds were used when there was no trip on the alternative lane during the 15-minute interval in which trip was made. These average speeds were calculated using actual trips that occurred on these lanes during the same time frame (off-peak, shoulder and peak) over the month (weekdays only). Table 2 shows average speeds used to determine travel times in the event no data was available on the alternate lanes in that 15-minute time period.

Table 2 Speed Comparison by Period

Period	Average Speed on the Toll Lanes (in mph)	Average Speed on the GPLs (in mph)
Peak Period (7–9 a.m. Eastbound and 4–6 p.m. Westbound)	53.2	42.8
Shoulder (6–7 a.m. and 9–10 a.m. Eastbound and 3–4 a.m. and 6–7 p.m. Westbound)	61.3	55.6
Off-Peak Period (All Other Times)	68.1	65.3

Note: The speed comparisons are for the entire trip identified, which may include short parts of the trip that are outside the 12 miles of the toll lane.

3.3.4 Lane Changes and the HOV Lane

Vehicles were only detected at the sensors. Therefore, for a vehicle that had changed the lane from GPL to ML, or vice versa, along the ML segment of Katy Freeway, it was impossible to determine the exact location of the lane switch. As a result, travel time savings could not be estimated. Consequently, those trips that switched between the GPL and ML, or vice versa, were deleted from dataset.

The goal of this research was to understand travelers' lane choice behavior by analyzing their choices between tolled and free lanes. Therefore, all trips on the HOV lanes during HOV-free hours were removed as these trips were toll free. Moreover, only weekday, non-holiday trips were included in the analysis while weekend and holiday trips were excluded from the dataset. Therefore, data for first Friday of the month (4/6/2012) which was Good Friday for 2012 was excluded from any analysis. All of these adjustments reduced the total trips for April from 3,530,623 trips to 2,283,433 trips.

3.3.5 Final Dataset

The final dataset, which was used in this research, had two records for each trip. The two records represented the two choices for the trip: one that was made and one on the lanes not chosen. The trip parameters included in the final dataset were the random ID, lane choice, trip time, total toll paid, trip length, lane blockages, heavy rain, and peak, off-peak, or shoulder period. Table 3 shows a few rows of the final data set.

In Table 3, ID is the observation's number and Randid is the randomized number assigned to each transponder ID (actual transponder IDs were deleted to make

identifying the original transponder owner impossible). The lane choice column indicates which trip was the actual trip (lane choice=1) and which trip was the shadow trip (lane choice=0). The time, toll and length columns show the travel time (in minutes), the toll (in dollars) and the length (in miles) of the trips, respectively. Start sensor and end sensor are the start location and end location of the trips along the freeway. Peak and shoulder are dummy variables indicating whether the trip was made during the peak period (peak=1) and whether the trip was made during the peak or shoulder period (shoulder=1), respectively. In other words, when peak=1 and shoulder=1, it's the peak period; and when peak=0 and shoulder=1, it's the shoulder period. Start time column shows the start time of the trips using SAS DATETIME format. SAS DATETIME format counts the number of seconds since January, 1, 1960. For example, one second after midnight on January 2, 1960 would be shown by 86401 in this format. Mldum shows whether the trip was on MLs (mldum=1); either the actual trip or the shadow trip should be on MLs. Mlblock and gplblock show the number of blocked MLs and GPLs downstream of the start location of the trip when the trip was started. Finally, rain is a dummy variable with the value of 1 for trips during the four hours of April 2012 in which hourly rainfall was greater than 0.4 inch.

In the next section of the thesis, the focus is on analyzing the final dataset and trying to explain travelers' behavior.

Table 3 Few Rows of the Trip Dataset

ID	Randid	Lane	Time	Toll	Length	Start sensor	End sensor	Peak	Sho- ulder	Starttime	MLdum	MLblock	Gplblock	Rain
1	998999216	0	1.90	0.3	2.35	105	426	0	0	1650815097	1	0	0	0
1	998999216	1	2.17	0	2.63	440	426	0	0	1650815097	0	0	0	0
2	998999216	0	2.42	0.3	2.35	105	426	0	0	1650834877	1	0	0	0
2	998999216	1	2.12	0	2.63	440	426	0	0	1650834877	0	0	0	0
3	998998644	0	2.59	0.3	4.06	460	456	0	0	1649930251	1	0	0	0
3	998998644	1	3.63	0	4.06	425	445	0	0	1649930251	0	0	0	0
4	998998644	0	1.75	0.3	2.35	105	426	0	0	1649936044	1	0	0	0
4	998998644	1	2.15	0	2.63	440	426	0	0	1649936044	0	0	0	0
5	998996223	0	4.66	1.2	2.11	460	107	1	1	1649698723	1	0	0	0
5	998996223	1	1.22	0	1.06	425	441	1	1	1649698723	0	0	0	0
6	998996223	0	4.21	0.6	4.53	105	5	0	1	1651396523	1	0	0	0
6	998996223	1	6.57	0	4.81	440	5	0	1	1651396523	0	0	0	0
7	998994433	0	2.01	0.3	1.95	107	456	0	0	1650198250	1	0	0	0
7	998994433	1	3.05	0	3	441	445	0	0	1650198250	0	0	0	0
8	998994433	0	1.54	0.3	1.95	453	105	0	0	1650919703	1	0	0	0
8	998994433	1	1.42	0	1.67	444	440	0	0	1650919703	0	0	0	0
9	998994433	0	1.87	1.2	1.95	107	456	1	1	1650993612	1	0	0	0
9	998994433	1	3.30	0	3	441	445	1	1	1650993612	0	0	0	0
10	998993761	0	3.33	0.3	2.35	105	426	0	0	1649609684	1	0	0	0
10	998993761	1	2.20	0	2.63	440	426	0	0	1649609684	0	0	0	0
11	998991551	0	0.97	0.3	2.11	460	107	0	0	1649156018	1	0	0	0
11	998991551	1	0.83	0	1.06	425	441	0	0	1649156018	0	0	0	0
12	998991551	0	1.54	0.3	1.95	453	105	0	0	1650492240	1	0	0	0
12	998991551	1	1.45	0	1.67	444	440	0	0	1650492240	0	0	0	0
13	998989036	0	4.03	1.2	4.3	468	105	1	1	1649056323	1	0	0	0
13	998989036	1	5.23	0	4.02	466	440	1	1	1649056323	0	0	0	0
14	998989036	0	5.58	0.6	6.41	460	469	0	0	1649099828	1	0	0	0
14	998989036	1	6.05	0	6.41	425	467	0	0	1649099828	0	0	0	0

4. DATA ANALYSIS

This section of the thesis describes how data were analyzed to have an understanding of trip attributes on both MLs and GPLs; then in an attempt to find the best measurement of reliability, models for different times of day using different measures of reliability were developed. In order to gain preliminary insight into travel times in MLs and GPLs, average travel time and standard deviation of travel time for a vehicle traveling the entire 12 mile section of Katy freeway with MLs were calculated (see Table 4).

Table 4 Average Travel Time and Travel Time Standard Deviation by Period

Period	Average Travel Time on MLs (min)	Average Travel Time on GPLs (min)	Standard Deviation of Travel Time on MLs (min)	Standard Deviation of Travel Time on GPLs (min)
Peak Period	13.88	19.52	4.24	7.06
Shoulder Period	11.47	14.35	2.55	5.04
Off-Peak Period	10.31	11.59	1.95	3.21

To account for exogenous factors, average travel time and standard deviation of travel time for each day were also calculated (see Table 5). As it can be seen in the table, average travel time and standard deviation of travel time are almost the same for the whole month. Both Table 4 and 5 show small travel time savings and reliability improvements for MLs over the GPLs during the off-peak period.

Table 5 Average Travel Time and Travel Time Standard Deviation by Day

Date	Day of Week	Lane Set	Average Travel time			Standard Deviation of Travel Time		
			Peak	Shoulder	Off-Peak	Peak	Shoulder	Off-Peak
4/2/2012	Monday	MLs	13.26	11.21	10.40	3.26	1.77	1.73
		GPLs	20.14	14.47	11.38	8.57	4.86	2.05
4/3/2012	Tuesday	MLs	13.52	11.65	10.32	3.81	3.06	1.97
		GPLs	19.40	14.31	11.47	7.13	5.56	2.35
4/4/2012	Wednesday	MLs	14.41	11.71	10.29	4.25	3.19	1.85
		GPLs	20.93	14.61	11.47	7.92	5.59	2.18
4/5/2012	Thursday	MLs	14.05	11.68	10.42	4.05	2.88	2.42
		GPLs	19.19	14.54	12.82	6.04	4.68	6.90
4/9/2012	Monday	MLs	13.74	11.24	10.25	5.34	2.50	2.05
		GPLs	18.22	13.69	11.34	6.93	4.55	3.03
4/10/2012	Tuesday	MLs	14.17	11.85	10.21	4.25	2.96	1.79
		GPLs	19.65	14.47	11.17	7.00	4.92	1.56
4/11/2012	Wednesday	MLs	13.31	11.27	10.38	3.02	1.87	1.98
		GPLs	18.49	13.52	11.57	5.79	3.49	2.43
4/12/2012	Thursday	MLs	14.38	11.39	10.26	3.86	2.49	1.82
		GPLs	20.86	14.32	11.66	6.80	4.77	2.97
4/13/2012	Friday	MLs	13.93	10.99	10.29	4.27	1.70	2.01
		GPLs	20.27	13.63	11.49	5.18	3.73	2.30
4/16/2012	Monday	MLs	12.43	11.00	10.51	2.61	1.81	2.17
		GPLs	16.13	13.12	11.71	5.21	3.35	2.10
4/17/2012	Tuesday	MLs	13.63	11.42	10.19	3.85	2.44	1.79
		GPLs	19.61	14.83	11.36	7.96	6.35	2.16
4/18/2012	Wednesday	MLs	14.39	11.40	10.24	4.42	2.17	1.84
		GPLs	20.62	14.67	11.52	7.46	5.69	2.81
4/19/2012	Thursday	MLs	14.69	12.13	10.25	5.07	3.99	1.79
		GPLs	21.00	15.71	11.64	7.13	6.32	3.04
4/20/2012	Friday	MLs	15.83	12.20	10.50	6.22	2.68	2.33
		GPLs	21.17	15.91	12.61	8.36	5.51	6.54
4/23/2012	Monday	MLs	13.53	11.30	10.30	4.01	2.25	1.89
		GPLs	19.64	14.07	11.08	7.50	5.30	1.36
4/24/2012	Tuesday	MLs	13.63	11.46	10.26	3.71	2.28	1.72
		GPLs	18.95	14.50	11.29	6.98	5.08	1.81
4/25/2012	Wednesday	MLs	14.14	11.72	10.32	4.75	2.56	1.89
		GPLs	19.40	14.12	11.43	5.74	3.67	2.00
4/26/2012	Thursday	MLs	14.58	11.47	10.45	4.96	2.55	2.10
		GPLs	19.69	14.23	12.01	6.68	4.78	4.37
4/27/2012	Friday	MLs	13.37	10.85	10.31	3.62	1.29	1.81
		GPLs	17.40	13.01	11.47	5.21	2.92	1.97
4/30/2012	Monday	MLs	12.91	11.48	10.27	3.07	2.63	1.93
		GPLs	20.01	15.31	11.17	6.88	6.50	1.62

To have an overall understanding of travelers' choices, the percentage of trips in each lane set in each period were determined (see Table 6). The percentage of trips with a paid toll on the MLs is larger in the peak period and decreases from peak period to shoulder period and from shoulder period to off-peak period. This is likely a result of smaller travel time savings and travel time reliability improvement in the MLs versus the GPLs during the shoulder period and off-peak period, as shown in Table 4 and 5.

Table 6 Classification of Trips by Time of Day

Time Period	Paid Trips*		GPL Trips		Total Trips**
	Count	Percentage	Count	Percentage	
Peak Period	84,079	3.68	298,758	13.08	382,837
Shoulder	39,716	1.74	292,252	12.80	331,968
Off-Peak Period	59,358	2.60	1,509,270	66.10	1,568,628
Total Trips	183,153	8.02	2,100,280	91.98	2,283,433

* Paid trips on the MLs made by SOVs and HOVs during non-HOV-free hours

** Total trips excludes trips made by vehicles without transponder IDs, trips on the HOV lanes during HOV-free hours, and trips detected on both MLs and GPLs in the 12 mile portion of the freeway that includes MLs.

4.1 Reliability Measures

Several ways of measuring reliability were used in this research. Table 7 includes all of the reliability measures used in this research.

Table 7 Reliability Measures

Reliability Measure	Description	Equation
Standard Deviation (SD)	Measures the extent of dispersion of travel time	$\sqrt{\frac{1}{N} \sum_{i=1}^N (x_i - \mu)^2}$
Coefficient of Variation (CV)	Provides normalized measure of dispersion	$CV = \frac{SD}{\mu}$
95 th Percentile	Indicates the value below which 95 percentage of travel times fall	
Shorten Right Range (SRR)	Shows delay for the heaviest travel condition	90 th percentile travel time - median travel time
Interquartile Range (IR)	Disregards extreme travel times and measure overall travel time variability	75 th percentile - 25 th percentile travel time
Travel Time Index (TTI)	Compares mean time it takes to travel to free flow conditions	$\frac{\text{Average travel time}}{\text{Free flow travel time}}$
Buffer Time Index (BTI)	Indicates the extra time that must be added to average travel time when planning trips to ensure on-time arrival	$\frac{95^{th} \text{ percentile} - \text{Average travel time}}{\text{Average travel time}}$
Planning Time Index (PTI)	Total time needed to plan for an on-time arrival 95% of the time	$\frac{95^{th} \text{ percentile travel time}}{\text{Free flow travel time}}$
Misery Index (MI)	Measures how bad are the worst trips	$\frac{\text{Average travel time for the longest 20\% of trip} - \text{Average travel time}}{\text{Average travel time}}$
Percent of Trips with Unacceptable Delays (PT)	Percent of trips with travel time greater than the median travel time plus 20 percent of the median	
Bad Trip Experience	Shows if traveler had any unacceptable trip in his/her previous trips	
Last Trip Indicator	Shows if traveler's last trip was unacceptable	

A definition of travel time reliability is: the consistency in travel times from day-to-day across different times of the day (FHWA, 2014). Therefore, reliability measures shown in Table 7 need to be calculated over the month for different time periods. To

calculate those reliability measures, mean, standard deviation and percentiles of travel time over the month for different time periods are needed. These statistical terms should be calculated for trips with the same length. One option is to calculate these terms for the trips with same start location and end location during the same time period over the month. However, the main goal of this research is to find the value of reliability in travelers' perception and it may not be realistic to assume that travelers have an estimation of reliability based on the exact start location and end location of a trip on the freeway. They are more likely to have an estimation of reliability for MLs and GPLs based on the length of a trip.

In order to calculate reliability measures based on overall travelers' experiences on the Freeway, the travel time per mile (travel time divided by trip distance) was calculated for each trip. For the trips that were made on the same lane set and during the same time interval (one hour interval for off peak periods and 30 minute interval for peak and shoulder periods) over the month, mean, standard deviation and percentiles of the travel time per mile were calculated. Then for each trip, the attributes of travel time per mile were multiplied by the length of the trip to find the trip travel time mean, standard deviation and percentiles and be able to obtain the measures shown in Table 7. For example, for all trips that were made from 12:00 pm to 1:00 pm over the month, travel times per mile were calculated. Then statistical terms (mean, standard deviation and percentiles) were calculated for trips on the MLs and trips on the GPLs. As a last step, these statistical terms were multiplied by the length of the trips to obtain the reliability measures shown in Table 7.

For this approach to yield reasonable estimates of the measures in Table 7, travel time and standard deviation of travel time per mile must be fairly uniform along the freeway during each period. To check for uniformity, the freeway was divided into three segments (see Table 8) and average travel time per mile and standard deviation of travel time per mile were calculated for each segment for each period (see Table 9).

Average travel time and standard deviation of travel time per mile are almost the same for all three segments (see Table 9). The small differences in travel time per mile for the different segments would be imperceptible to drivers who choose between MLs and GPLs based on their overall experiences in each lane set.

Table 8 Segments of Katy Freeway

		Eastbound	Westbound
GPLs	Segment 1	sensor 427 to sensor 443	sensor 442 to sensor 396
	Segment 2	sensor 443 to sensor 444	sensor 445 to sensor 442
	Segment 3	sensor 444 to sensor 426	sensor 425 to sensor 445
MLs	Segment 1	sensor 449 to sensor 451	sensor 458 to sensor 459
	Segment 2	sensor 451 to sensor 453	sensor 456 to sensor 458
	Segment 3	sensor 453 to sensor 426	sensor 460 to sensor 456

Table 9 Average and Standard Deviation of Travel Time per Mile for Segments

		Peak Period		Shoulder Period		Off-Peak Period	
		Average Travel Time per Mile (min)	Standard Deviation of Travel time per Mile (min)	Average Travel Time per Mile (min)	Standard Deviation of Travel time per Mile (min)	Average Travel Time per Mile (min)	Standard Deviation of Travel time per Mile (min)
GPLs	Segment 1	1.94	0.61	1.36	0.55	0.86	0.10
	Segment 2	2.00	0.80	1.35	0.60	0.94	0.14
	Segment 3	1.87	0.64	1.16	0.43	0.94	0.16
MLs	Segment 1	1.37	0.35	1.06	0.29	0.79	0.07
	Segment 2	1.18	0.36	0.94	0.18	0.90	0.11
	Segment 3	1.28	0.31	0.90	0.15	0.79	0.14

4.2 Logit Models

Discrete choice models can be used to analyze and predict a decision maker's choice from a set of alternatives. In discrete choice models, a utility function is defined for all the available alternatives. The standard utility function is shown in Equation 25.

$$U_i = V_i + \varepsilon_i \quad (25)$$

Where U_i = Utility of alternative i

ε_i = The error term or unknown portion of the utility

V_i = Observable portion of the utility = $\sum \beta_k X_k$

Where β_k = the parameter that defines the direction and importance of the effect of attribute K on the utility of alternative i

X_k = the value of attribute k for alternative i

The error term included in the utility function accounts for the fact that it is not possible to completely and correctly measure or specify all attributes that impact travelers' utility assessment. A wide range of distributions can be used to represent the error term.

Three assumptions about the error term would lead to a multinomial logit model: (1) the error components have Gumble distributions (2) the error components are identically and independently distributed across alternatives (3) the error components are identically and independently distributed across individuals.

Statistical Analysis System (SAS) was used to generate multinomial discrete-choice models (see code in Appendix). The independent variables in the multinomial logit models are focused on travel conditions. The traveler's characteristics are not included in the models as such data were not available. Lane-choice models were developed based on travelers' lane of choice:

$$U_{GPL} = \beta_{TT} \text{TravelTime}_{GPL} + \beta_{TTR} \text{TravelTimeReliability}_{GPL} + \beta_{GLB} \text{GPLsBlocked}_{GPL} + \beta_{Rain} \text{Rain}$$

$$U_{ML} = \beta_{ML} + \beta_{Toll} \text{Toll} + \beta_{TT} \text{TravelTime}_{ML} + \beta_{TTR} \text{TravelTimeReliability}_{ML} + \beta_{MLB} \text{MLsBlocked}$$

Where: ML = Managed Lane

GPL = General Purpose Lane

TT = Travel Time

TTR = Travel Time Reliability

GLB = GPLs Blocked

MLB = MLs Blocked

Table 10 shows the logit model developed for the data set. All variables except travel time reliability were included in the models. It can be seen that the coefficients of time and toll do not change when variables indicating rain and lane closure are added to the model. The signs of the coefficients of rain and gplsblock are not reasonable. The

models suggest that in the case of heavy rain or an accident in the GPLs, travelers are more likely to use the GPLs (which is counter-intuitive). Because adding rain and lane closure variables do not impact the coefficients of time and toll, these variables were excluded from the models.

Table 10 Logit Models Including Lane Closure and Rain Variables

Variable	Coefficient	t Value	Approx Pr> t
<i>Model: $U_{TOLL} = B_1 \times time + B_2 \times toll + B_3 \times mblock$, $U_{GPL} = B_1 \times time + B_2 \times toll + B_4 \times gplblock + B_5 \times rain$</i>			
Time	-0.23	-241.37	<.0001
Toll	-1.96	-624.62	<.0001
MLsBlocked	-1.59	-20.65	<.0001
GPLsBlocked	1.49	49.75	<.0001
Rain	2.46	48.58	<.0001
<i>Model: $U_{TOLL} = B_1 \times time + B_2 \times toll + B_3 \times mblock$, $U_{GPL} = B_1 \times time + B_2 \times toll + B_4 \times gplblock$</i>			
Time	-0.23	-241.91	<.0001
Toll	-1.97	-627.15	<.0001
MLsBlocked	-1.59	-20.61	<.0001
GPLsBlocked	1.50	50.04	<.0001
<i>Model: $U_{TOLL} = B_1 \times time + B_2 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times toll + B_3 \times rain$</i>			
Time	-0.23	-238.49	<.0001
Toll	-1.96	-627.20	<.0001
Rain	2.48	48.86	<.0001
<i>Model: $U_{TOLL} = B_1 \times time + B_2 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times toll$</i>			
Time	-0.23	-239.06	<.0001
Toll	-1.97	-629.77	<.0001

Models were developed for the whole month, peak period only, shoulder period only, and off-peak periods only. Table 11 includes the logit models when only time and toll are included as independent variables. When an alternative specific coefficient is not included, the model shows negative coefficients for time and toll. In addition, the VOT

obtained from the model (using Equation 3) is reasonable and increases from off-peak periods (\$2.78/hr) to shoulder periods (\$9.09/hr) to peak periods (\$10.52/hr). This indicates that travelers' VOT is higher during the peak hour which is consistent with the literature. Using the whole dataset for the entire month over the entire day, VOT was found to be \$7.00/hr. However, adding the alternative specific preference coefficient (ASC) to the model changes the results significantly. The toll coefficient becomes positive, which is counter-intuitive.

Table 12 to Table 21 include logit models with time, toll and reliability as independent variables. In each table one of the reliability measures is used. It was expected that time, toll and measures of the (un)reliability should have negative coefficients, indicating an increase in each of them leads to a decrease in utility. However, most of the models have a positive coefficient for at least one of them, which is counter-intuitive. Tables 12, 14, 15, 16, 17 and 19 include standard deviation, 95th percentile, interquartile range, shorten right range, travel time index and planning time index as reliability measures. Each of those models with ASC, time and reliability has a negative coefficient for the reliability measure and time. Although a reliability ratio can be obtained from such a model, since there is no toll variable, the value of time and reliability cannot be estimated.

Table 11 Logit Models with Time and Toll as Independent Variables

Variable	Coefficient			
	All Month	Peak Period	Shoulder	Off-Peak
<i>Model: $U_{TOLL} = B_1 \times time + B_2 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times toll$</i>				
Time	-0.23*	-0.10*	-0.20*	-0.31*
Toll	-1.97*	-0.57*	-1.32*	-6.68*
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times toll$</i>				
ASC_ML	-3.81*	-3.24*	-3.27*	-4.36*
Time	-0.18*	-0.15*	-0.13*	-0.29*
Toll	0.90*	0.72*	0.71*	1.27*

*Statistically significant at 0.05 significance level ($p < 0.05$).

Table 12 Logit Models with the Standard Deviation (SD) as Reliability Measure

Variable	Coefficient			
	All Month	Peak Period	Shoulder	Off-Peak
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times SD + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times SD + B_3 \times toll$</i>				
ASC_ML	-3.92*	-3.39*	-3.37*	-4.57*
Time	-0.12*	-0.10*	-0.10*	-0.19*
SD (Unreliability)	-0.38*	-0.32*	-0.29*	-0.40*
Toll	0.78*	0.64*	0.58*	1.43*
<i>Model: $U_{TOLL} = B_1 \times time + B_2 \times SD + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times SD + B_3 \times toll$</i>				
Time	-0.19*	-0.10*	-0.24*	-0.24*
SD (Unreliability)	-0.22*	0.01*	0.44*	-0.34*
Toll	-2.07*	-0.57*	-1.05*	-6.92*
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times SD$, $U_{GPL} = B_1 \times time + B_2 \times SD$</i>				
ASC_ML	-3.31*	-2.40*	-2.96*	-3.79*
Time	-0.22*	-0.12*	-0.16*	-0.27*
SD (Unreliability)	-0.46*	-0.46*	-0.50*	-0.39*

*Statistically significant at 0.05 significance level ($p < 0.05$).

Table 13 Logit Models with the Coefficient of Variation (CV) as Reliability Measure

Variable	Coefficient			
	All Month	Peak Period	Shoulder	Off-Peak
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times CV + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times CV + B_3 \times toll$</i>				
ASC ML	-4.06*	-3.17*	-3.37*	-4.83*
Time	-0.16*	-0.15*	-0.13*	-0.20*
CV (Unreliability)	-5.12*	1.03*	-1.25*	-6.26*
Toll	0.89*	0.72*	0.71*	1.71*
<i>Model: $U_{TOLL} = B_1 \times time + B_2 \times CV + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times CV + B_3 \times toll$</i>				
Time	-0.23*	-0.14*	-0.15*	-0.28*
CV (Unreliability)	0.23*	14.81*	27.53*	-2.68*
Toll	-1.97*	-0.29*	-0.07*	-6.81*
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times CV$, $U_{GPL} = B_1 \times time + B_2 \times CV$</i>				
ASC ML	-3.26*	-1.83*	-2.68*	-3.86*
Time	0.29*	-0.20*	-0.24*	-0.31*
CV (Unreliability)	-4.55*	2.70*	-1.91*	-5.50*

*Statistically significant at 0.05 significance level ($p < 0.05$).

Table 14 Logit Models with the 95th Percentile as Reliability Measure

Variable	Coefficient			
	All Month	Peak Period	Shoulder	Off-Peak
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times 95th + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times 95th + B_3 \times toll$</i>				
ASC ML	-3.92*	-3.43*	-3.31*	-4.59*
Time	-0.09*	-0.08*	-0.10*	-0.16*
95 th Percentile (Unreliability)	-0.14*	-0.10*	-0.06*	-0.19*
Toll	0.70*	0.63*	0.58*	1.21*
<i>Model: $U_{TOLL} = B_1 \times time + B_2 \times 95th + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times 95th + B_3 \times toll$</i>				
Time	-0.19*	-0.09*	-0.22*	-0.22*
95 th Percentile (Unreliability)	-0.07*	-0.02*	0.04*	-0.15*
Toll	-2.12*	-0.60*	-1.23*	-7.10*
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times 95th$, $U_{GPL} = B_1 \times time + B_2 \times 95th$</i>				
ASC ML	-3.45*	-2.49*	-2.91*	-3.94*
Time	-0.15*	-0.09*	-0.14*	-0.23*
95 th Percentile (Unreliability)	-0.19*	-0.14*	-0.14*	-0.19*

*Statistically significant at 0.05 significance level ($p < 0.05$).

Table 15 Logit Models with the Interquartile Range (IR) as Reliability Measure

Variable	Coefficient			
	All Month	Peak Period	Shoulder	Off-Peak
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times IR + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times IR + B_3 \times toll$</i>				
ASC_ML	-3.74*	-3.40*	-3.28*	-4.57*
Time	-0.12*	-0.11*	-0.12*	-0.17*
IR (Unreliability)	-0.24*	-0.18*	-0.14*	-1.06*
Toll	0.63*	0.60*	0.55*	1.28*
<i>Model: $U_{TOLL} = B_1 \times time + B_2 \times IR + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times IR + B_3 \times toll$</i>				
Time	-0.11*	-0.11*	-0.19*	-0.23*
IR (Unreliability)	-0.80*	0.01*	-0.12*	-0.89*
Toll	-2.81*	-0.56*	-1.46*	-7.04*
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times IR$, $U_{GPL} = B_1 \times time + B_2 \times IR$</i>				
ASC_ML	-3.33*	-2.58*	-2.89*	-3.88*
Time	-0.16*	-0.12*	-0.16*	-0.25*
IR (Unreliability)	-0.42*	-0.27*	-0.29*	-1.06*

*Statistically significant at 0.05 significance level ($p < 0.05$).

Table 16 Logit Models with the Shorten Right Range (SRR) as Reliability Measure

Variable	Coefficient			
	All Month	Peak Period	Shoulder	Off-Peak
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times SRR + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times SRR + B_3 \times toll$</i>				
ASC_ML	-3.91*	-3.32*	-3.34*	-4.59*
Time	-0.12*	-0.12*	-0.11*	-0.19*
SRR (Unreliability)	-0.16*	-0.09*	-0.09*	-0.22*
Toll	0.79*	0.68*	0.60*	1.37*
<i>Model: $U_{TOLL} = B_1 \times time + B_2 \times SRR + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times SRR + B_3 \times toll$</i>				
Time	-0.20*	-0.10*	-0.21*	-0.25*
SRR (Unreliability)	-0.07*	-0.01*	0.10*	0.18*
Toll	-2.06*	-0.57*	-1.15*	-7.00*
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times SRR$, $U_{GPL} = B_1 \times time + B_2 \times SRR$</i>				
ASC_ML	-3.31*	-2.21*	-2.93*	-3.84*
Time	-0.22*	-0.15*	-0.18*	-0.27*
SRR (Unreliability)	-0.21*	-0.13*	-0.20*	-0.21*

*Statistically significant at 0.05 significance level ($p < 0.05$).

Table 17 Logit Models with the Travel Time Index (TTI) as Reliability Measure

Variable	Coefficient			
	All Month	Peak Period	Shoulder	Off-Peak
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times TTI + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times TTI + B_3 \times toll$</i>				
ASC_ML	-4.04*	-3.09*	-3.03*	-5.38*
Time	-0.16*	-0.15*	-0.13*	-0.19*
TTI (Unreliability)	-2.11*	0.33*	1.81*	-6.47*
Toll	0.66*	0.73*	0.84*	1.73*
<i>Model: $U_{TOLL} = B_1 \times time + B_2 \times TTI + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times TTI + B_3 \times toll$</i>				
Time	-0.27*	-0.13*	-0.19*	-0.34*
TTI (Unreliability)	4.75*	6.50*	12.17*	3.43*
Toll	-1.13*	0.71*	0.57*	-5.88*
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times TTI$, $U_{GPL} = B_1 \times time + B_2 \times TTI$</i>				
ASC_ML	-3.85*	-2.83*	-2.78*	-4.34*
Time	-0.22*	-0.20*	-0.22*	-0.30*
TTI (Unreliability)	-3.90*	-1.82*	-1.18*	-5.66*

*Statistically significant at 0.05 significance level ($p < 0.05$).

Table 18 Logit Models with the Buffer Time Index (BTI) as Reliability Measure

Variable	Coefficient			
	All Month	Peak Period	Shoulder	Off-Peak
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times BTI + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times BTI + B_3 \times toll$</i>				
ASC_ML	-4.04*	-3.20*	-3.17*	-4.94*
Time	-0.17*	-0.15*	-0.12*	-0.20*
BTI (Unreliability)	-2.52*	0.35*	0.93*	-4.55*
Toll	0.88*	0.72*	0.73*	1.65*
<i>Model: $U_{TOLL} = B_1 \times time + B_2 \times BTI + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times BTI + B_3 \times toll$</i>				
Time	-0.24*	-0.13*	-0.14*	-0.29*
BTI (Unreliability)	2.98*	4.41*	5.49*	-1.18*
Toll	-1.75*	-0.42*	-0.68*	-6.85*
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times BTI$, $U_{GPL} = B_1 \times time + B_2 \times BTI$</i>				
ASC_ML	-3.30*	-1.89*	-2.57*	-4.00*
Time	-0.30*	-0.19*	-0.24*	-0.30*
BTI (Unreliability)	-2.57*	0.87*	-0.25*	-4.05*

*Statistically significant at 0.05 significance level ($p < 0.05$).

Table 19 Logit Models with the Planning Time Index (PTI) as Reliability Measure

Variable	Coefficient			
	All Month	Peak Period	Shoulder	Off-Peak
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times PTI + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times PTI + B_3 \times toll$</i>				
ASC_ML	-4.07*	-3.00*	-2.99*	-5.08*
Time	-0.16*	-0.15*	-0.13*	-0.19*
PTI (Unreliability)	-0.97*	0.28*	0.94*	-1.74*
Toll	0.70*	0.73*	0.86*	1.70*
<i>Model: $U_{TOLL} = B_1 \times time + B_2 \times PTI + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times PTI + B_3 \times toll$</i>				
Time	-0.25*	-0.15*	-0.16*	-0.30*
PTI (Unreliability)	0.92*	2.70*	3.99*	-0.17*
Toll	-1.63*	0.42*	0.20*	-6.76*
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times PTI$, $U_{GPL} = B_1 \times time + B_2 \times PTI$</i>				
ASC_ML	-3.68*	-1.99*	-2.74*	-4.09*
Time	-0.24*	-0.19*	-0.23*	-0.30*
PTI (Unreliability)	-1.46*	-0.02*	-0.44*	-1.54*

*Statistically significant at 0.05 significance level ($p < 0.05$).

Table 20 Logit Models with the Misery Index (MI) as Reliability Measure

Variable	Coefficient			
	All Month	Peak Period	Shoulder	Off-Peak
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times MI + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times MI + B_3 \times toll$</i>				
ASC_ML	-4.09*	-3.15*	-3.64*	-4.82*
Time	-0.18*	-0.15*	-0.14*	-0.20*
MI (Unreliability)	-3.78*	-0.84*	-2.02*	-5.10*
Toll	0.84*	0.73*	0.71*	1.67*
<i>Model: $U_{TOLL} = B_1 \times time + B_2 \times MI + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times MI + B_3 \times toll$</i>				
Time	-0.23*	-0.10*	-0.07*	-0.28*
MI (Unreliability)	0.12*	7.78*	12.59*	-2.26*
Toll	-1.97*	-0.23*	-0.01	-6.83*
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times MI$, $U_{GPL} = B_1 \times time + B_2 \times MI$</i>				
ASC_ML	-3.38*	-2.17*	-2.89*	-3.29*
Time	-0.30*	-0.21*	-0.25*	-0.36*
MI (Unreliability)	-3.96*	0.86*	-1.98*	1.37*

*Statistically significant at 0.05 significance level ($p < 0.05$).

Table 21 Logit Models with the Percent of Unacceptable Trips (PT) as Reliability Measure

Variable	Coefficient			
	All Month	Peak Period	Shoulder	Off-Peak
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times PT + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times PT + B_3 \times toll$</i>				
ASC_ML	-3.90*	-3.11*	-3.04*	-4.94*
Time	-0.15*	-0.16*	-0.12*	-0.22*
PT (Unreliability)	-2.09*	0.90*	2.56*	-12.09*
Toll	0.80*	0.70*	0.82*	1.68*
<i>Model: $U_{TOLL} = B_1 \times time + B_2 \times PT + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times PT + B_3 \times toll$</i>				
Time	-0.22*	-0.18*	-0.15*	-0.29*
PT (Unreliability)	-0.67*	8.25*	19.20*	-3.21*
Toll	-2.00*	-0.22*	0.57*	-6.80*
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times PT$, $U_{GPL} = B_1 \times time + B_2 \times PT$</i>				
ASC_ML	-3.36*	-1.69*	-2.91*	-3.98*
Time	-0.24*	-0.21*	-0.22*	-0.32*
PT (Unreliability)	-5.36*	2.41*	-2.81*	-10.74*

*Statistically significant at 0.05 significance level ($p < 0.05$).

Next, any correlation between time and reliability measures, investigated as a high correlation between independent variables of the model, would result in misleading coefficients of the correlated variables

4.3 Correlation between Travel Time and Reliability Measures

Correlations between time and all reliability measures were obtained for the dataset (see Table 22). It can be seen that travel time has a high correlation (correlation coefficient between 0.6 and 1) with several measures of reliability, including standard deviation, 95th percentile, short right range and interquartile range. This indicates that as travel time increases the width of travel time distribution increases as well. All travel time reliability measures have one thing in common; they increase as the width of travel time distribution increases. However, since it was found that as travel time increases the

width of travel time distribution increases, normalized reliability measures that measure the relative width of travel time distributions should be used. Table 22 shows that travel time has a low correlation (correlation coefficient between 0 and 0.3) with the coefficient of variation, travel time index, buffer time index, misery index and percent of unacceptable trips. These are normalized measures of variability which means that they allow the spread of a travel time distribution with a large mean and a correspondingly large spread to be compared with the spread of a travel time distribution with a smaller mean and a correspondingly smaller spread. As an example, to compare reliability of two routes, one with 10 minute average travel time and 5 minute standard deviation of travel time, and the other one with 5 minute average travel time and 4 minute standard deviation of travel time, the coefficient of variation would be a better measure of reliability than standard deviation as it compares relative width of distributions. Those normalized measures are used in models developed in the next steps because of their lower correlation with travel time.

Table 22 Correlation between Time and Reliability Measures

Pearson Correlation Coefficients (r) Prob> r under H0: Correlation=0*											
	Time	SD	CV	95th	SRR	IR	TTI	BTI	PTI	MI	PT
Time	1.00	0.74	0.08	0.91	0.66	0.69	0.21	0.11	0.18	0.11	0.18
		<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
SD	0.74	1.00	0.56	0.92	0.97	0.90	0.55	0.55	0.59	0.56	0.54
	<.001		<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
CV	0.08	0.56	1.00	0.30	0.59	0.46	0.71	0.93	0.83	0.93	0.80
	<.001	<.001		<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
95th	0.91	0.92	0.30	1.00	0.88	0.86	0.40	0.34	0.40	0.34	0.36
	<.001	<.001	<.001		<.001	<.001	<.001	<.001	<.001	<.001	<.001
SRR	0.66	0.97	0.59	0.88	1.00	0.91	0.62	0.65	0.67	0.63	0.61
	<.001	<.001	<.001	<.001		<.001	<.001	<.001	<.001	<.001	<.001
IR	0.69	0.90	0.46	0.86	0.91	1.00	0.67	0.51	0.65	0.52	0.62
	<.001	<.001	<.001	<.001	<.001		<.001	<.001	<.001	<.001	<.001
TTI	0.21	0.55	0.71	0.40	0.62	0.67	1.00	0.79	0.97	0.78	0.84
	<.001	<.001	<.001	<.001	<.001	<.001		<.001	<.001	<.001	<.001
BTI	0.11	0.55	0.93	0.34	0.65	0.51	0.79	1.00	0.90	0.95	0.85
	<.001	<.001	<.001	<.001	<.001	<.001	<.001		<.001	<.001	<.001
PTI	0.18	0.59	0.83	0.40	0.67	0.65	0.97	0.90	1.00	0.88	0.89
	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001		<.001	<.001
MI	0.11	0.56	0.93	0.34	0.63	0.52	0.78	0.95	0.88	1.00	0.90
	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001		<.001
PT	0.18	0.54	0.80	0.36	0.61	0.62	0.84	0.85	0.89	0.90	1.00
	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	

*Prob > |r| under H0: Correlation=0 - is the p-value and indicates the probability of observing this correlation coefficient under the null hypothesis (H0) that the correlation is 0.

4.4 Discrete Choice Models for Travelers who Alternated their Lane Choice

There is a chance that Katy Freeway travelers do not make lane choices based on the variables used in discrete choice models including travel time or travel time reliability. There might be a group of travelers who always choose to drive on GPLs no matter how bad the traffic on these lanes is. The reason can be inherent opposition toward the MLs or unwillingness to weave in and out of MLs. On the other hand, some travelers may always avoid GPLs. These travelers do not actually make a decision about

which lane to use as they have a predefined approach toward MLs, regardless of travel time savings or travel time reliability.

There were 167,665 travelers who had more than five trips in April 2012. Among those, 130,768 travelers never used the MLs and 736 travelers never used the GPLs. Overall, 131,504 travelers never changed their lane type. Data regarding the trips of these travelers were excluded from the next analysis. Logit models were developed for those 36,161 travelers who had more than five trips in the month and changed their lane of choice at least once. Those reliability measures which were found to have low correlation with travel time (see Section 4.3) were used to estimate logit models. As seen in Table 23 to Table 28, none of the models, in which both the measure of reliability and toll are included, had negative coefficients for the measure of reliability and the toll for all periods. Therefore, these models are considered to be counter-intuitive as they are counter-intuitive.

Table 23 Logit Models with the Coefficient of Variation (CV) as Reliability Measure for Travelers Who Alternated Their Lane Choice

Variable	Coefficient			
	All Month	Peak Period	Shoulder	Off-Peak
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times CV + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times CV + B_3 \times toll$</i>				
ASC_ML	-2.56*	-1.34*	-1.86*	-3.21*
Time	-0.17*	-0.13*	-0.15*	-0.24*
CV (Unreliability)	-6.62*	1.11*	-1.18*	-8.02*
Toll	0.86*	0.59*	0.64*	1.40*
<i>Model: $U_{TOLL} = B_1 \times time + B_2 \times CV + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times CV + B_3 \times toll$</i>				
Time	-0.14*	-0.12*	-0.14*	-0.28*
CV (Unreliability)	-1.89*	6.83*	12.77*	-4.74*
Toll	-0.35*	0.19*	0.22*	-3.08*
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times CV$, $U_{GPL} = B_1 \times time + B_2 \times CV$</i>				
ASC_ML	-1.79*	-0.24*	-1.20*	-2.24*
Time	-0.30*	-0.18*	-0.25*	-0.35*
CV (Unreliability)	-6.24*	2.28*	-1.56*	-7.19*

*Statistically significant at 0.05 significance level ($p < 0.05$).

Table 24 Logit Models with the Travel Time Index (TTI) as Reliability Measure for Travelers Who Alternated Their Lane Choice

Variable	Coefficient			
	All Month	Peak Period	Shoulder	Off-Peak
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times TTI + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times TTI + B_3 \times toll$</i>				
ASC_ML	-2.58*	-1.68*	-1.65*	-3.86*
Time	-0.16*	-0.14*	-0.15*	-0.22*
TTI (Unreliability)	-3.17*	-0.61*	0.85*	-8.05*
Toll	0.48*	0.59*	0.70*	1.37*
<i>Model: $U_{TOLL} = B_1 \times time + B_2 \times TTI + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times TTI + B_3 \times toll$</i>				
Time	-0.15*	-0.12*	-0.17*	-0.31*
TTI (Unreliability)	1.04*	2.59*	5.57*	-1.12*
Toll	-0.14*	0.55*	0.48*	-3.11*
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times TTI$, $U_{GPL} = B_1 \times time + B_2 \times TTI$</i>				
ASC_ML	-2.41*	-1.32*	-1.41*	-3.02*
Time	-0.21*	-0.18*	-0.22*	-0.33*
TTI (Unreliability)	-4.40*	-2.02*	-1.58*	-7.29*

*Statistically significant at 0.05 significance level ($p < 0.05$).

Table 25 Logit Models with the Buffer Time Index (BTI) as Reliability Measure for Travelers Who Alternated Their Lane Choice

Variable	Coefficient			
	All Month	Peak Period	Shoulder	Off-Peak
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times BTI + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times BTI + B_3 \times toll$</i>				
ASC ML	-2.58*	-1.38*	-1.69*	-3.32*
Time	-0.17*	-0.13*	-0.14*	-0.24*
BTI (Unreliability)	-3.43*	0.28*	0.72*	-5.73*
Toll	0.85*	0.60*	0.66*	1.30*
<i>Model: $U_{TOLL} = B_1 \times time + B_2 \times BTI + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times BTI + B_3 \times toll$</i>				
Time	-0.15*	-0.11*	-0.13*	-0.28*
BTI (Unreliability)	0.64*	1.87*	4.18*	-2.93*
Toll	-0.28*	0.13*	0.08*	-3.22*
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times BTI$, $U_{GPL} = B_1 \times time + B_2 \times BTI$</i>				
ASC ML	-1.83*	-0.30*	-1.10*	-2.58*
Time	-0.31*	-0.18*	-0.25*	-0.34*
BTI (Unreliability)	-3.31*	0.62*	-0.19*	-5.25*

*Statistically significant at 0.05 significance level ($p < 0.05$).

Table 26 Logit Models with the Planning Time Index (PTI) as Reliability Measure for Travelers Who Alternated Their Lane Choice

Variable	Coefficient			
	All Month	Peak Period	Shoulder	Off-Peak
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times PTI + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times PTI + B_3 \times toll$</i>				
ASC ML	-2.62*	-1.33*	-1.61*	-3.49*
Time	-0.16*	-0.14*	-0.15*	-0.23*
PTI (Unreliability)	-1.37*	0.09*	0.51*	-2.17*
Toll	0.58*	0.60*	0.71*	1.34*
<i>Model: $U_{TOLL} = B_1 \times time + B_2 \times PTI + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times PTI + B_3 \times toll$</i>				
Time	-0.15*	-0.12*	-0.15*	-0.29*
PTI (Unreliability)	0.10*	1.12*	2.44*	-0.88*
Toll	-0.28*	0.46*	0.48*	-3.25*
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times PTI$, $U_{GPL} = B_1 \times time + B_2 \times PTI$</i>				
ASC ML	-2.28*	-0.47*	-1.36*	-2.70*
Time	-0.23*	-0.18*	-0.23*	-0.34*
PTI (Unreliability)	-1.77*	-0.12*	-0.58*	-1.98*

*Statistically significant at 0.05 significance level ($p < 0.05$).

Table 27 Logit Models with the Misery Index (MI) as Reliability Measure for Travelers Who Alternated Their Lane Choice

Variable	Coefficient			
	All Month	Peak Period	Shoulder	Off-Peak
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times MI + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times MI + B_3 \times toll$</i>				
ASC_ML	-2.57*	-1.29*	-2.14*	-3.18*
Time	-0.18*	-0.13*	-0.16*	-0.24*
MI (Unreliability)	-4.75*	1.21*	-2.04*	-6.54*
Toll	0.76*	0.60*	0.64*	1.35*
<i>Model: $U_{TOLL} = B_1 \times time + B_2 \times MI + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times MI + B_3 \times toll$</i>				
Time	-0.15*	-0.11*	-0.11*	-0.28*
MI (Unreliability)	-1.51*	4.35*	6.06*	-4.20*
Toll	-0.38*	0.25*	0.27*	-3.08*
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times MI$, $U_{GPL} = B_1 \times time + B_2 \times MI$</i>				
ASC_ML	-1.92*	-0.26*	-1.42*	-2.42*
Time	-0.31*	-0.18*	-0.26*	-0.35*
MI (Unreliability)	-5.11*	0.91*	-1.94*	-6.00*

*Statistically significant at 0.05 significance level ($p < 0.05$).

Table 28 Logit Models with the Percent of Unacceptable Trips (PT) as Reliability Measure for Travelers Who Alternated Their Lane Choice

Variable	Coefficient			
	All Month	Peak Period	Shoulder	Off-Peak
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times PT + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times PT + B_3 \times toll$</i>				
ASC_ML	-2.37*	-1.21*	-1.65*	-3.30*
Time	-0.15*	-0.14*	-0.15*	-0.23*
PT (Unreliability)	-4.24*	1.46*	1.25*	-14.66*
Toll	0.70*	0.58*	0.69*	1.38*
<i>Model: $U_{TOLL} = B_1 \times time + B_2 \times PT + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times PT + B_3 \times toll$</i>				
Time	-0.14*	-0.15*	-0.15*	-0.28*
PT (Unreliability)	-1.49*	4.38*	9.16*	-7.06*
Toll	-0.37*	0.25*	0.52*	-3.07*
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times PT$, $U_{GPL} = B_1 \times time + B_2 \times PT$</i>				
ASC_ML	-1.86*	-0.09*	-1.47*	-2.53*
Time	-0.24*	-0.19*	-0.23*	-0.35*
PT (Unreliability)	-6.00*	2.32*	-2.82*	-13.33*

*Statistically significant at 0.05 significance level ($p < 0.05$).

For those 31,161 travelers who changed their lane of choice at least once, logit models with only time and toll as independent variables were also developed to find the VOT for this group of travelers.

As seen in Table 29, when the ASC is not included in the model, the toll variable has a negative coefficient for the entire dataset, shoulder period and off-peak period. The marginal rate of substitution of time shows VOT to be \$29.03/hr, \$33.10/hr and \$6.59/hr for the entire data set, shoulder period and off-peak period. These are significantly different from VOT obtained before excluding those travelers who do not switch their lane choice between MLs and GPLs. Also, for the peak period, the model has a positive coefficient for the toll. These differences may be due to changes in the percent of travelers using MLs in the new dataset as compared to the previous analyses (section 4.2).

A total of 484,755 trips were made by those 31,161 travelers who changed their lane of choice at least once (see Table 30). For these trips, the percent of trips on the MLs is much larger than the percent of ML usage when all trips are included in the dataset, especially during the peak period. Therefore, it can be concluded that this approach biases the sample toward ML use and does not properly represent the driving population.

Table 29 Logit Models with Time and Toll as Independent Variables for Travelers Who Alternated Their Lane Choice

Variable	Coefficient (Standard Error)			
	All Month	Peak Period	Shoulder	Off-Peak
<i>Model: $U_{TOLL} = B_1 \times time + B_2 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times toll$</i>				
Time	-0.15*	-0.10*	-0.16*	-0.32*
Toll	-0.31*	0.08*	-0.29*	-2.91*
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times toll$</i>				
ASC_ML	-2.25*	-1.41*	-1.77*	-2.55*
Time	-0.18*	-0.13*	-0.15*	-0.31*
Toll	0.84*	0.60*	0.64*	0.78*

*Statistically significant at 0.05 significance level ($p < 0.05$).

Table 30 Classification of Trips by Travelers Who Alternated Their Lane Choice by Time of Day

Time Period	Paid Trips		GPL Trips		Total Trips
	Count	Percentage	Count	Percentage	
Peak Period	69,159	14.27	50,611	10.44	119,770
Shoulder	31,681	6.54	52,485	10.83	84,166
Off-Peak Period	44,349	9.15	236,470	48.78	280,819
Total Trips	145,189	29.95	339,566	70.05	484,755

4.5 The Influence of an Unacceptable Trip Experience

In section 4.4 travelers who have a specific approach toward MLs and do not switch between MLs and GPLs were excluded. However, excluding those travelers did not improve the mode choice models with reliability measures. Rather, it appears to have made the models with only time and toll as independent variables even worse. Another option is that those travelers who never changed their lane choice are satisfied with their trips. In other words, a trip on the GPLs during the peak period might take 50 percent longer than free flow conditions, but this might match the traveler's expectation and the

traveler justifies his\her departure time based on this knowledge. Therefore, we next examined if having a particularly bad trip, an unacceptable trip, helped explain lane choice.

In this analysis, a trip was considered to be unacceptable if it took more than 1.4 times the median travel time for a similar trip. As explained in section 4.1, in order to obtain the median travel time, for each trip, the travel time per mile (travel time divided by trip distance) was calculated. For the trips that were on the same lane type during the same time interval (one hour interval for off peak periods and 30 minute interval for peak and shoulder periods) over the month, 50th percentile of the travel time per mile was calculated. Then, for each trip, the 50th percentile of travel time per mile was multiplied by the length of the trip. As discussed in section 4.1, the alternative was to calculate the 50th percentile of travel times for trips with the same start location and end location for each period. However, travelers are more likely to have an estimation of median travel time based on the length of the trip and the type of lane rather than different estimations of median travel time based on the exact section of the freeway in which trip was made. Considering that the goal is to find the value of reliability in travelers' perception, the former approach was used in this research.

A dummy variable, which shows whether a traveler had an unacceptable trip in his or her previous trips, was added to the trip attributes. For example, if a traveler experienced an unacceptable trip on the GPLs on his fifth trip in April, the dummy variable would be one for the GPLs, indicating having a bad trip experience on that lane set, for all trips after the fifth trip. Logit models including time, toll and bad trip experience (BTE) as independent variables were developed.

As it can be seen in Table 31, BTE (having a bad trip experience) has a positive coefficient in the utility functions for all developed models. It might be because of the inertia or unwillingness to change one's traveling behaviors including lane choice. In other words, travelers prefer not to change their lane even though they had experienced unacceptable trips on that lane set. It could also be a result of a wrong definition for an unacceptable trip. Other definitions such as a trip longer than 2 times the median travel time or longer than 80th percentile of travel time were tried; however, no improvement to the models was achieved (see Table 32 and Table 33).

Table 31 Logit Models with Bad Trip Experience (BTE) Indicator as the Measure of Reliability (Bad Trip Is a Trip Longer than 1.4 Times the Median Travel Time)

Variable	Coefficient			
	All Month	Peak Period	Shoulder	Off-Peak
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times BTE + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times BTE + B_3 \times toll$</i>				
ASC_ML	-3.77*	-3.06*	-3.16*	-4.27*
Time	-0.18*	-0.16*	-0.14*	-0.30*
BTE (Unreliability)	1.87*	2.05*	1.92*	1.48*
Toll	0.97*	0.77*	0.75*	1.27*
<i>Model: $U_{TOLL} = B_1 \times time + B_2 \times BTE + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times BTE + B_3 \times toll$</i>				
Time	-0.24*	-0.12*	-0.21*	-0.33*
BTE (Unreliability)	2.14*	2.24*	2.22*	1.54*
Toll	-1.78*	-0.45*	-1.16*	-6.40*
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times BTE$, $U_{GPL} = B_1 \times time + B_2 \times BTE$</i>				
ASC_ML	-2.99*	-1.75*	-2.38*	-3.59*
Time	-0.34*	-0.21*	-0.26*	-0.37*
BTE (Unreliability)	1.83*	2.02*	1.90*	1.48*

*Statistically significant at 0.05 significance level ($p < 0.05$).

Table 32 Logit Models with Bad Trip Experience (BTE) Indicator as Reliability Measure (Bad Trip Is a Trip Longer than 2 Times the Median Travel Time)

Variable	Coefficient			
	All Month	Peak Period	Shoulder	Off-Peak
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times BTE + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times BTE + B_3 \times toll$</i>				
ASC_ML	-3.80*	-3.20*	-3.25*	-4.32*
Time	-0.18*	-0.15*	-0.13*	-0.29*
BTE (Unreliability)	1.77*	2.00*	1.79*	1.35*
Toll	0.91*	0.73*	0.71*	1.25*
<i>Model: $U_{TOLL} = B_1 \times time + B_2 \times BTE + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times BTE + B_3 \times toll$</i>				
Time	-0.23*	-0.11*	-0.20*	-0.32*
BTE (Unreliability)	2.13*	2.12*	2.09*	1.48*
Toll	-1.92*	-0.54*	-1.29*	-6.58*
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times BTE$, $U_{GPL} = B_1 \times time + B_2 \times BTE$</i>				
ASC_ML	-3.05*	-1.92*	-2.50*	-2.65*
Time	-0.32*	-0.20*	-0.24*	-0.37*
BTE (Unreliability)	1.77*	1.95*	1.79*	1.36*

*Statistically significant at 0.05 significance level ($p < 0.05$).

Table 33 Logit Models with Bad Trip Experience (BTE) Indicator as Reliability Measure (Bad Trip Is a Trip Longer than 80th Percentile Travel Time)

Variable	Coefficient			
	All Month	Peak Period	Shoulder	Off-Peak
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times BTE + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times BTE + B_3 \times toll$</i>				
ASC_ML	-3.57*	-2.90*	-3.00*	-4.06*
Time	-0.19*	-0.16*	-0.15*	-0.31*
BTE (Unreliability)	1.89*	2.04*	1.98*	1.63*
Toll	0.92*	0.74*	0.71*	1.17*
<i>Model: $U_{TOLL} = B_1 \times time + B_2 \times BTE + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times BTE + B_3 \times toll$</i>				
Time	-0.25*	-0.13*	-0.22*	-0.36*
BTE (Unreliability)	2.49*	2.30*	2.37*	1.98*
Toll	-1.54*	-0.42*	-1.09*	-5.88*
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times BTE$, $U_{GPL} = B_1 \times time + B_2 \times BTE$</i>				
ASC_ML	-2.83*	-1.66*	-2.27*	-3.43*
Time	-0.33*	-0.21*	-0.26*	-0.39*
BTE (Unreliability)	1.94*	2.05*	2.01*	1.68*

*Statistically significant at 0.05 significance level ($p < 0.05$).

4.7 Unacceptable Last Trip Experience

In section 4.5 a dummy variable was defined that indicates whether a traveler had any extremely bad trip in his or her previous trips or not. However, this variable found to have a positive coefficient in the utility functions, which is not reasonable. There is a chance that travelers' lane choice is mainly affected by their most recent trip. For example, if a traveler had a bad experience on his third trip on the GPLs but his fourth and fifth trips on the GPLs were fine, then probably his bad experience would not impact his lane choice on his sixth trip.

A trip is considered to be unacceptable if it takes more than 1.4 times the median travel time for a similar trip. A dummy variable, which shows whether a traveler's last trip was acceptable or not, was added to the trip attributes. For example, if a traveler had an unacceptable trip on the GPLs on his third trip in April, for his fourth trip, the dummy variable would be one for the GPLs, indicating the last trip on GPLs was unacceptable. Logit models including time, toll and last trip indicator (LTI) as independent variables were developed.

As it can be seen in Table 34, LTI (having a bad trip experience in the last trip) has a positive coefficient in the utility function for all developed models. It again might be because of the inertia or unwillingness to change the traveling behaviors including the lane choice. In other words, travelers prefer not to change their lane of choice although their last trip on that lane set was unacceptable. It could also be a result of a wrong definition for an unacceptable trip. Other definitions such as a trip longer than 2 times the median travel time or longer than 80th percentile of travel time were tried; however, no improvement to the models was achieved (see Table 35 and Table 36).

Table 34 Logit Models with Last Trip Indicator (LTI) as Reliability Measure (Bad Trip Is a Trip Longer than 1.4 Times the Median Travel Time)

Variable	Coefficient			
	All Month	Peak Period	Shoulder	Off-Peak
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times LTI + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times LTI + B_3 \times toll$</i>				
ASC_ML	-3.80*	-3.19*	-3.26*	-4.35*
Time	-0.17*	-0.15*	-0.13*	-0.29*
LTI (Unreliability)	1.71*	1.82*	1.79*	1.38*
Toll	0.91*	0.73*	0.73*	1.27*
<i>Model: $U_{TOLL} = B_1 \times time + B_2 \times LTI + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times LTI + B_3 \times toll$</i>				
Time	-0.23*	-0.11*	-0.20*	-0.31*
LTI (Unreliability)	1.98*	2.02*	2.02*	1.39*
Toll	-1.93*	-0.54*	-1.28*	-6.63*
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times LTI$, $U_{GPL} = B_1 \times time + B_2 \times LTI$</i>				
ASC_ML	-3.06*	-1.92*	-2.50*	-3.66*
Time	-0.32*	-0.20*	-0.24*	-0.37*
LTI (Unreliability)	1.68*	1.78*	1.76*	1.37*

*Statistically significant at 0.05 significance level ($p < 0.05$).

Table 35 Logit Models with Last Trip Indicator (LTI) as Reliability Measure (Bad Trip Is a Trip Longer than 2 Times the Median Travel Time)

Variable	Coefficient			
	All Month	Peak Period	Shoulder	Off-Peak
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times LTI + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times LTI + B_3 \times toll$</i>				
ASC_ML	-3.81*	-3.23*	-3.28*	-4.36*
Time	-0.18*	-0.15*	-0.13*	-0.29*
LTI (Unreliability)	1.83*	2.04*	1.87*	1.44*
Toll	0.90*	0.73*	0.71*	1.27*
<i>Model: $U_{TOLL} = B_1 \times time + B_2 \times LTI + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times LTI + B_3 \times toll$</i>				
Time	-0.23*	-0.10*	-0.20*	-0.31*
LTI (Unreliability)	2.14*	2.06*	2.03*	1.46*
Toll	-1.97*	-0.56*	-1.31*	-6.66*
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times LTI$, $U_{GPL} = B_1 \times time + B_2 \times LTI$</i>				
ASC_ML	-3.08*	-1.96*	-2.53*	-3.68*
Time	-0.31*	-0.20*	-0.24*	-0.37*
LTI (Unreliability)	1.85*	1.97*	1.85*	1.44*

*Statistically significant at 0.05 significance level ($p < 0.05$).

Table 36 Logit Models with Last Trip Indicator (LTI) as Reliability Measure (Bad Trip Is a Trip Longer than 80th Percentile Travel Time)

Variable	Coefficient			
	All Month	Peak Period	Shoulder	Off-Peak
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times LTI + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times LTI + B_3 \times toll$</i>				
ASC_ML	-3.72*	-3.14*	-3.19*	-4.25*
Time	-0.18*	-0.15*	-0.13*	-0.30*
LTI (Unreliability)	1.59*	1.64*	1.70*	1.39*
Toll	0.90*	0.73*	0.72*	1.23*
<i>Model: $U_{TOLL} = B_1 \times time + B_2 \times LTI + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times LTI + B_3 \times toll$</i>				
Time	-0.23*	-0.11*	-0.20*	-0.33*
LTI (Unreliability)	2.26*	1.93*	2.10*	1.73*
Toll	-1.82*	-0.52*	-1.24*	-6.41*
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times LTI$, $U_{GPL} = B_1 \times time + B_2 \times LTI$</i>				
ASC_ML	-2.99*	-1.87*	-2.45*	-3.60*
Time	-0.32*	-0.20*	-0.24*	-0.38*
LTI (Unreliability)	1.64*	1.65*	1.72*	1.43*

*Statistically significant at 0.05 significance level ($p < 0.05$).

4.8 One Trip for Each Traveler

It was found that a large portion of travelers always choose the same lane and do not make different choices. Mostly they choose the GPLs for all their trips. However, excluding those travelers who never change lanes from the dataset failed to produce reasonable discrete choice models and biased the data set. On the other hand, including all trips of those travelers in the dataset inappropriately models all persons' trips as independent decisions. For example, a traveler may have fifty trips in April and use GPLs in all his fifty trips. However, the model developing process treats these fifty trips as fifty unrelated trips.

In statistics and econometrics, the term *panel data* refers to such dataset that involves more than one observation over different times for the same individuals.

Standard logit model does not take into account those unobserved factors that are the same over time for a particular traveler. To account for the correlation in unobserved factors over time, mixed logit models should be used. However, the large size of dataset does not allow using mixed logit models. Moreover, the software that was used in this research, Statistical Analysis System (SAS), was unable to account for panel data in developing mixed logit models. Therefore, the only benefit of mixed logit models over standard logit model developed by SAS is that mixed logit model accounts for the random taste variation and heterogeneity across travelers (see section 4.8).

One way to examine the impact of this issue is to select one trip for each traveler as a sample. The last trip of each traveler who had more than 5 trips in April was selected. Travelers with less than five trips in a month may not be familiar with travel time and so travel time reliability of MLs and GPLs and were excluded.

Logit models were developed for the new dataset including the last trip of each traveler who had more than five trips in April 2012 (see Table 37). When ASC is not included in the model, both time and toll have negative coefficients. The models estimate travelers' VOT to be \$10.90/hr, \$8.77/hr and \$2.77/hr for peak period, shoulder period and off peak period, respectively. These values are similar to VOTs extracted from Table 11, where all the trips were used to develop logit models.

In Table 38 to 43, different reliability measures (only those which were found to have low correlation with time) were added to the models developed in Table 37. For all models in which both time and toll were included, either the toll or reliability measure had a positive coefficient in one of the time periods. When the toll is not included in the

models, the reliability measure has a negative coefficient for all periods when the travel time index and planning time index are used as reliability measures (see Table 39 and 41). From these models it can be interpreted that travelers probably do not care about the exact amount of toll they have to pay, and the fact that they need to pay a toll is what actually impacts their decision.

ASC is defined as a dummy variable which is 1 for MLs and 0 for GPLs. If more than two alternatives were available, ASC would have been 0 for one of them and 1 for the rest. In this research case, where only two options are available, one tolled and one free, introducing ASC to the model is the same as introducing a variable which is one when travelers have to pay. Therefore, considering that models including ASC, time and reliability as independent variables have reasonable coefficients, it can be interpreted that travelers may not care about the exact toll: it is the fact that they have to pay a toll that impacts their decision. However, before making any conclusion, in the next section mixed logit models are developed to account for heterogeneity across travelers to see if models including the toll variable will improve or not.

Table 37 Logit Models for the Last Trip of Travelers with More than 5 Trips with Time and Toll as Independent Variables

Variable	Coefficient			
	All Month	Peak Period	Shoulder	Off-Peak
<i>Model: $U_{TOLL} = B_1 \times time + B_2 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times toll$</i>				
Time	-0.29*	-0.10*	-0.19*	-0.31*
Toll	-2.26*	-0.55*	-1.30*	-6.72*
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times toll$</i>				
ASC ML	-3.88*	-3.34*	-3.28*	-4.28*
Time	-0.15*	-0.14*	-0.09*	-0.26*
Toll	1.04*	0.89*	0.80*	1.22*

*Statistically significant at 0.05 significance level ($p < 0.05$).

Table 38 Logit Models for the Last Trip of Travelers with More than 5 Trips with the Coefficient of Variation (CV) as Reliability Measure

Variable	Coefficient			
	All Month	Peak Period	Shoulder	Off-Peak
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times CV + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times CV + B_3 \times toll$</i>				
ASC ML	-4.12*	-3.22*	-3.23*	-4.81*
Time	-0.14*	-0.15*	-0.09*	-0.20*
CV (Unreliability)	-5.31*	1.93*	0.64*	-6.49*
Toll	1.04*	0.88*	0.80*	1.68*
<i>Model: $U_{TOLL} = B_1 \times time + B_2 \times CV + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times CV + B_3 \times toll$</i>				
Time	-0.29*	-0.13*	-0.12*	-0.29*
CV (Unreliability)	-0.03	16.57*	30.04*	-2.76*
Toll	-2.26*	-0.19*	0.11*	-6.89*
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times CV$, $U_{GPL} = B_1 \times time + B_2 \times CV$</i>				
ASC ML	-3.30*	-1.80*	-2.54*	-3.88*
Time	-0.29*	-0.20*	-0.20*	-0.33*
CV (Unreliability)	-4.85*	3.15*	-0.82*	-5.78*

*Statistically significant at 0.05 significance level ($p < 0.05$).

Table 39 Logit Models for the Last Trip of Travelers with More than 5 Trips with the Travel Time Index (TTI) as Reliability Measure

Variable	Coefficient			
	All Month	Peak Period	Shoulder	Off-Peak
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times TTI + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times TTI + B_3 \times toll$</i>				
ASC_ML	-4.15*	-3.13*	-3.14*	-5.41*
Time	-0.13*	-0.14*	-0.09*	-0.19*
TTI (Unreliability)	-2.47*	0.49*	0.97*	-6.80*
Toll	0.77*	0.90*	0.87*	1.68*
<i>Model: $U_{TOLL} = B_1 \times time + B_2 \times TTI + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times TTI + B_3 \times toll$</i>				
Time	-0.33*	-0.12*	-0.18*	-0.32*
TTI (Unreliability)	4.63*	6.87*	11.01*	2.99*
Toll	-1.43*	0.87*	0.44*	-5.97*
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times TTI$, $U_{GPL} = B_1 \times time + B_2 \times TTI$</i>				
ASC_ML	-3.90*	-2.84*	-2.81*	-3.50*
Time	-0.20*	-0.20*	-0.18*	-0.36*
TTI (Unreliability)	-4.19*	-1.90*	-1.59*	-6.06*

*Statistically significant at 0.05 significance level ($p < 0.05$).

Table 40 Logit Models for the Last Trip of Travelers with More than 5 Trips with the Buffer Time Index (BTI) as Reliability Measure

Variable	Coefficient			
	All Month	Peak Period	Shoulder	Off-Peak
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times BTI + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times BTI + B_3 \times toll$</i>				
ASC_ML	-4.12*	-3.26*	-3.17*	-4.94*
Time	-0.14*	-0.15*	-0.08*	-0.20*
BTI (Unreliability)	-2.70*	0.75*	1.12*	-4.74*
Toll	1.03*	0.88*	0.84*	1.61*
<i>Model: $U_{TOLL} = B_1 \times time + B_2 \times BTI + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times BTI + B_3 \times toll$</i>				
Time	-0.30*	-0.13*	-0.14*	-0.30*
BTI (Unreliability)	2.55*	5.47*	4.69*	-1.22*
Toll	-2.05*	-0.34*	-0.75*	-6.92*
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times BTI$, $U_{GPL} = B_1 \times time + B_2 \times BTI$</i>				
ASC_ML	-3.35*	-1.85*	-2.53*	-4.04*
Time	-0.29*	-0.20*	-0.20*	-0.32*
BTI (Unreliability)	-2.84*	1.17*	-0.35*	-4.27*

*Statistically significant at 0.05 significance level ($p < 0.05$).

Table 41 Logit Models for the Last Trip of Travelers with More than 5 Trips with the Planning Time Index (PTI) as Reliability Measure

Variable	Coefficient			
	All Month	Peak Period	Shoulder	Off-Peak
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times PTI + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times PTI + B_3 \times toll$</i>				
ASC_ML	-4.17*	-2.98*	-3.06*	-5.09*
Time	-0.13*	-0.14*	-0.09*	-0.20*
PTI (Unreliability)	-1.08*	0.43*	0.67*	-1.83*
Toll	0.82*	0.91*	0.91*	1.66*
<i>Model: $U_{TOLL} = B_1 \times time + B_2 \times PTI + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times PTI + B_3 \times toll$</i>				
Time	-0.31*	-0.14*	-0.16*	-0.30*
PTI (Unreliability)	0.85*	2.98*	3.53*	-0.20*
Toll	-1.94*	0.62*	0.08*	-6.83*
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times PTI$, $U_{GPL} = B_1 \times time + B_2 \times PTI$</i>				
ASC_ML	-3.72*	-2.01*	-2.78*	-4.14*
Time	-0.23*	-0.20*	-0.18*	-0.32*
PTI (Unreliability)	-1.53*	-0.05*	-0.62*	-1.64*

*Statistically significant at 0.05 significance level ($p < 0.05$).

Table 42 Logit Models for the Last Trip of Travelers with More than 5 Trips with the Misery Index (MI) as Reliability Measure

Variable	Coefficient			
	All Month	Peak Period	Shoulder	Off-Peak
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times MI + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times MI + B_3 \times toll$</i>				
ASC_ML	-4.15*	-3.25*	-3.39*	-4.80*
Time	-0.15*	-0.14*	-0.09*	-0.20*
MI (Unreliability)	-3.91*	0.95*	-0.66*	-5.29*
Toll	0.98*	0.89*	0.80*	1.62*
<i>Model: $U_{TOLL} = B_1 \times time + B_2 \times MI + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times MI + B_3 \times toll$</i>				
Time	-0.29*	-0.10*	-0.06*	-0.30*
MI (Unreliability)	-0.10*	7.97*	13.38*	-2.31*
Toll	-2.27*	-0.18*	0.07*	-6.92*
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times MI$, $U_{GPL} = B_1 \times time + B_2 \times MI$</i>				
ASC_ML	-3.40*	-1.92*	-2.66*	-3.92*
Time	-0.30*	-0.20*	-0.20*	-0.33*
MI (Unreliability)	-4.07*	0.39*	-1.08*	-4.80*

*Statistically significant at 0.05 significance level ($p < 0.05$).

Table 43 Logit Models for the Last Trip of Travelers with More than 5 Trips with the Percent of Unacceptable Trips (PT) as Reliability Measure

Variable	Coefficient			
	All Month	Peak Period	Shoulder	Off-Peak
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times PT + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times PT + B_3 \times toll$</i>				
ASC_ML	-3.96*	-3.16*	-3.01*	-4.87*
Time	-0.13*	-0.15*	-0.09*	-0.22*
PT (Unreliability)	-3.26*	1.15*	2.94*	-12.23*
Toll	0.91*	0.87*	0.93*	1.57*
<i>Model: $U_{TOLL} = B_1 \times time + B_2 \times PT + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times PT + B_3 \times toll$</i>				
Time	-0.28*	-0.17*	-0.13*	-0.29*
PT (Unreliability)	-1.64*	9.27*	18.94*	-3.86*
Toll	-2.34*	-0.06*	0.62*	-6.88*
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times PT$, $U_{GPL} = B_1 \times time + B_2 \times PT$</i>				
ASC_ML	-3.40*	-1.64*	-2.85*	-4.00*
Time	-0.23*	-0.21*	-0.18*	-0.34*
PT (Unreliability)	-5.87*	2.46*	-2.75*	-11.07*

*Statistically significant at 0.05 significance level ($p < 0.05$).

4.9 Mixed Logit Models

The mixed logit (or random parameter logit) model is a relatively recent development in discrete choice modeling. The mixed logit model is a strong modeling tool which can account for heterogeneity of individuals, scale differences in data sources, model repeated responses (panel data), modify error structures and heteroscedasticity from various sources (Bhat and Castelar, 2002).

The reason that the mixed logit model was used in this research was the idea that maybe the multinomial logit model fails to model travelers' choice as it does not account for the heterogeneity of travelers. Due to the complexity of the mixed logit model it was not possible to use it for a large dataset including all trips. However, it is possible to

develop mixed logit models for dataset that includes one trip (the last trip) for each traveler.

In the mixed logit models, to account for heterogeneity among travelers, coefficients can be random and vary across individuals. A coefficient chosen to vary across individuals can be specified as in Equation 26.

$$\beta = \beta^m + \beta^s \eta \quad (26)$$

In equation 26, β^m and β^s are the mean and scale parameter of the assumed distribution of the β , respectively. The stochastic component, η , is individual specific heterogeneity with a mean of zero and a standard deviation (scaled to) of one.

Travel time, travel time reliability and ASC parameters were chosen to vary across individuals and were assumed to have a normal distribution. Since parameters are assumed to have normal distributions, for each variable, the models give the mean value for its coefficient (M) and standard deviation of the coefficient (S) (the absolute value is the standard deviation).

Table 44 includes the mixed logit models including time and toll as the only independent variables. When ASC is not included in the model, the mean coefficient for time is positive which is counter-intuitive. This differs from the VOTs obtained using multinomial logit models. The range for the coefficient of time includes both negative and positive numbers. Since the distribution includes negative numbers, the results from the logit model and mixed logit model are not contradictory. However, the mean coefficient is positive which would lead to negative VOTs from the models. Besides, the standard deviation of the time coefficient is larger than zero; this shows the presence of

heterogeneity across travelers and suggests that the mixed logit model should be used to account for the heterogeneity.

In Tables 45 to 50, reliability measures were added to the models. It can be seen that none of the models had a negative coefficient for the toll, along with negative mean coefficients for time and reliability for all periods. It is not reasonable to assume that longer travel time or higher variability or larger cost increase travelers' utility for a model. Therefore, these models fail to explain travelers' lane choice decision.

Table 44 Mixed Logit Models with Time and Toll as Independent Variables

Variable	Coefficient			
	All Month	Peak Period	Shoulder	Off-Peak
<i>Model: $U_{TOLL} = B_1 \times time + B_2 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times toll$</i>				
Time-M	1.16*	0.19*	0.56*	0.38*
Time-S	-3.34*	-1.65*	2.42*	-1.59*
Toll	-4.99*	-1.09*	-2.81*	-8.05*
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times toll$</i>				
ASC ML-M	-7.68*	-3.37*	-7.21*	-5.66*
ASC ML-S	-2.97*	0.01	3.27*	1.67*
Time-M	-0.30*	-0.15*	-0.22*	-0.24*
Time-S	0.34*	0.05*	0.30*	-0.30*
Toll	2.10*	0.90*	1.74*	1.53*

*Statistically significant at 0.05 significance level ($p < 0.05$).

M= mean value, S= standard deviation.

Table 45 Mixed Logit Models with the Coefficient of Variation (CV) as Reliability Measure

Variable	Coefficient			
	All Month	Peak Period	Shoulder	Off-Peak
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times CV + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times CV + B_3 \times toll$</i>				
ASC ML-M	-8.41*	-3.25*	-5.98*	-7.11*
ASC ML-S	-3.06*	0.01	2.57*	2.09*
Time-M	-0.29*	-0.15*	-0.21*	-0.20*
Time-S	0.39*	0.04*	0.36*	-0.41*
CV-M (Unreliability)	-8.50*	1.91*	20.92*	-8.62*
CV-S	6.89*	-0.04	28.61*	3.90*
Toll	2.20*	0.90*	1.87*	2.35*
<i>Model: $U_{TOLL} = B_1 \times time + B_2 \times CV + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times CV + B_3 \times toll$</i>				
Time-M	1.17*	0.09*	-4.26*	0.41*
Time-S	3.35*	-0.95*	-6.68*	1.65*
CV-M (Unreliability)	-1.19*	23.98*	1346.00*	-3.88*
CV-S	-0.06	-0.05	856.87*	0.02
Toll	-5.04*	-0.36*	7.94*	-8.42*
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times CV$, $U_{GPL} = B_1 \times time + B_2 \times CV$</i>				
ASC ML-M	-4.57*	-1.86*	-4.67*	-4.65*
ASC ML-S	-1.48*	0.15*	2.48*	1.16*
Time-M	-0.34*	-0.23*	-0.36*	-0.23*
Time-S	0.57*	-0.01	0.54*	0.53*
CV-M (Unreliability)	-6.79*	6.48*	0.29*	-7.05*
CV-S	0.06	-11.31*	4.51*	0.51*

*Statistically significant at 0.05 significance level ($p < 0.05$).

M= mean value, S= standard deviation.

Table 46 Mixed Logit Models with Travel Time Index (TTI) as Reliability Measure

Variable	Coefficient			
	All Month	Peak Period	Shoulder	Off-Peak
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times TTI + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times TTI + B_3 \times toll$</i>				
ASC ML-S	-4.82*	-6.04*	-4.51*	-7.88*
ASC ML-M	-0.03*	0.58*	-4.31*	2.08*
Time-M	-0.30*	-0.43*	-0.48*	-0.19*
Time-S	-0.15*	0.01	-0.26*	-0.39*
TTI-M (Unreliability)	5.82*	9.80*	29.45*	-9.64*
TTI-S	-10.42*	-10.97*	23.64*	0.15*
Toll	1.68*	2.88*	3.05*	2.30*
<i>Model: $U_{TOLL} = B_1 \times time + B_2 \times TTI + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times TTI + B_3 \times toll$</i>				
Time-M	-2.14*	-0.76*	-2.05*	-1.21*
Time-S	-2.61*	0.11*	1.66*	-2.71*
TTI-M (Unreliability)	322.84*	44.36*	287.08*	502.99*
TTI-S	217.80*	-23.01*	166.45*	277.92*
Toll	-2.15*	5.40*	11.75*	-1.78*
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times TTI$, $U_{GPL} = B_1 \times time + B_2 \times TTI$</i>				
ASC-ML-M	-4.30*	-3.18*	-79.43*	-4.95*
ASC-ML-S	-0.44*	0.21*	45.47*	0.84*
Time-M	-0.48*	-0.32*	-9.43*	-0.21*
Time-S	0.19*	-0.02	6.76*	-0.48*
TTI-M (Unreliability)	2.54*	0.02*	104.37*	-6.99*
TTI-S	-10.68*	-4.58*	224.71*	0.17*

*Statistically significant at 0.05 significance level ($p < 0.05$).

M= mean value, S= standard deviation.

Table 47 Mixed Logit Models with Buffer Time Index (BTI) as Reliability Measure

Variable	Coefficient			
	All Month	Peak Period	Shoulder	Off-Peak
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times BTI + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times BTI + B_3 \times toll$</i>				
ASC ML-M	-7.59*	-3.28*	-7.01*	-7.95*
ASC ML-S	-2.52*	0.01	3.27*	2.45*
Time-M	-0.29*	-0.15*	-0.21*	-0.20*
Time-S	0.35*	0.04*	0.31*	0.48*
BTI-M (Unreliability)	1.53*	0.74*	2.20*	-7.37*
BTI-S	11.64*	-0.03	0.32*	-0.06*
Toll	2.14*	0.89*	1.84*	2.42*
<i>Model: $U_{TOLL} = B_1 \times time + B_2 \times BTI + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times BTI + B_3 \times toll$</i>				
Time-M	1.19*	0.02*	0.40*	0.36*
Time-S	-3.69*	-1.62*	-1.84*	1.56*
BTI-M (Unreliability)	35.75*	17.99*	4.87*	15.09*
BTI-S	55.69*	-18.47*	0.14*	23.30*
Toll	-6.13*	-0.99*	-1.88*	-8.67*
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times BTI$, $U_{GPL} = B_1 \times time + B_2 \times BTI$</i>				
ASC ML-M	-3.91*	-2.00*	-4.30*	-3.91*
ASC ML-S	-0.61*	0.09	2.13*	-0.62*
Time-M	-0.37*	-0.25*	-0.32*	-0.37*
Time-S	0.43*	-0.01	0.49*	0.43*
BTI-M (Unreliability)	1.70*	3.98*	-0.46*	1.71*
BTI-S	9.47*	-7.53*	0.17*	9.47*

*Statistically significant at 0.05 significance level ($p < 0.05$).

M= mean value, S= standard deviation.

Table 48 Mixed Logit Models with the Planning Time Index (PTI) as Reliability Measure

Variable	Coefficient			
	All Month	Peak Period	Shoulder	Off-Peak
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times PTI + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times PTI + B_3 \times toll$</i>				
ASC_ML-M	-6.46*	-3.12*	-6.63*	-7.97*
ASC_ML-S	-1.80*	0.12*	3.02*	2.35*
Time-M	-0.33*	-0.16*	-0.25*	-0.19*
Time-S	0.21*	-0.01	0.35*	0.45*
PTI-M (Unreliability)	1.73*	0.68*	2.67*	-2.77*
PTI-S	-4.47*	-0.83*	3.07*	-0.04
Toll	1.97*	0.99*	2.18*	2.42*
<i>Model: $U_{TOLL} = B_1 \times time + B_2 \times PTI + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times PTI + B_3 \times toll$</i>				
Time-M	-0.44*	-0.13*	0.59*	-0.49*
Time-S	-2.12*	-0.30*	7.21*	0.48*
PTI-M (Unreliability)	89.85*	22.87*	33.72*	160.38*
PTI-S	83.24*	-13.95*	37.14*	-88.71*
Toll	-8.94*	3.70*	-7.79*	-1.88*
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times PTI$, $U_{GPL} = B_1 \times time + B_2 \times PTI$</i>				
ASC_ML-M	-4.19*	-2.10*	-7.42*	-5.06*
ASC_ML-S	-0.12*	0.10	3.98*	1.26*
Time-M	-0.54*	-0.33*	-0.57*	-0.23*
Time-S	0.14*	-0.01	0.73*	0.51*
PTI-M (Unreliability)	2.48*	1.23*	-0.28*	-2.02*
PTI-S	6.00*	-2.31*	3.85*	-0.01

*Statistically significant at 0.05 significance level ($p < 0.05$).

M= mean value, S= standard deviation.

Table 49 Mixed Logit Models with the Misery Index (MI) as Reliability Measure

Variable	Coefficient			
	All Month	Peak Period	Shoulder	Off-Peak
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times MI + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times MI + B_3 \times toll$</i>				
ASC_ML-M	-8.48*	-3.28*	-7.33*	-9.03*
ASC_ML-S	-3.08*	0.02	3.10*	3.06*
Time-M	-0.31*	-0.15*	-0.22*	-0.23*
Time-S	0.40*	0.04*	0.35*	-0.55*
MI-M (Unreliability)	-6.70*	0.94*	3.17*	-9.53*
MI-S	4.45*	-0.50*	11.44*	-0.51*
Toll	2.09*	0.90*	1.89*	2.85*
<i>Model: $U_{TOLL} = B_1 \times time + B_2 \times MI + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times MI + B_3 \times toll$</i>				
Time-M	1.17*	0.06*	-0.57*	0.41*
Time-S	-3.36*	-1.04*	-0.04*	1.66*
MI-M (Unreliability)	-1.36*	12.20*	399.72*	-3.23*
MI-S	-0.08	-0.02	276.06*	0.04
Toll	-5.08*	-0.32*	4.75*	-8.48*
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times MI$, $U_{GPL} = B_1 \times time + B_2 \times MI$</i>				
ASC_ML-M	-5.08*	-1.93*	-5.62*	-5.72*
ASC_ML-S	-1.75*	0.02	2.94*	1.95*
Time-M	-0.36*	-0.20*	-0.43*	-0.28*
Time-S	0.63*	-0.01	0.69*	0.62*
MI-M (Unreliability)	-6.22*	0.50*	0.31*	-6.93*
MI-S	0.08	-1.59*	8.08*	0.13*

*Statistically significant at 0.05 significance level ($p < 0.05$).

M= mean value, S= standard deviation.

Table 50 Mixed Logit Models with the Percent of Unacceptable Trips (PT) as Reliability Measure

Variable	Coefficient			
	All Month	Peak Period	Shoulder	Off-Peak
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times PT + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times PT + B_3 \times toll$</i>				
ASC ML-M	-11.15*	-3.19*	-4.90*	-7.52*
ASC ML-S	-4.65*	0.02	-0.11*	2.16*
Time-M	-0.37*	-0.15*	-0.49*	-0.24*
Time-S	0.44*	0.04*	0.19*	-0.42*
PT-M (Unreliability)	-8.95*	1.14*	59.95*	-11.97*
PT-S	0.05	-0.06*	45.24*	11.97*
Toll	2.58*	0.88*	3.90*	2.37*
<i>Model: $U_{TOLL} = B_1 \times time + B_2 \times PT + B_3 \times toll$, $U_{GPL} = B_1 \times time + B_2 \times PT + B_3 \times toll$</i>				
Time-M	1.17*	-0.21*	2.20*	0.42*
Time-S	-3.42*	1.42*	7.31*	-1.66*
PT-M (Unreliability)	-3.01*	25.24*	180.94*	-5.75*
PT-S	-18.74*	-21.53*	98.61*	-0.01
Toll	-5.84*	-0.57*	2.43*	-8.42*
<i>Model: $U_{TOLL} = ASC_ML + B_1 \times time + B_2 \times PT$, $U_{GPL} = B_1 \times time + B_2 \times PT$</i>				
ASC ML-M	-5.65*	-1.83*	-3.54*	-4.67*
ASC ML-S	-2.12*	0.01	-0.05	0.95*
Time-M	-0.37*	-0.29*	-0.67*	-0.26*
Time-S	0.56*	-0.01	0.28*	-0.48*
PT-M (Unreliability)	-8.51*	5.73*	27.21*	-11.37*
PT-S	-6.94*	-8.36*	34.71*	8.28*

*Statistically significant at 0.05 significance level ($p < 0.05$).

M= mean value, S= standard deviation.

4.10 Data Analysis Summary

As the first step to explain Katy Freeway travelers' lane choice between MLs and GPLs, logit models were developed using different reliability measures. However, the models including toll, time and reliability had a positive coefficient for one of these variables for at least one period of time. In an attempt to improve the models, it was tried to exclude those travelers that did not change their lane from the dataset, most of those

models also included a positive coefficient for either toll, time or reliability. Plus this was a biased dataset.

New variables that indicate whether travelers had any unacceptable trips on a lane type in their previous trips and whether their last trip was acceptable or not were introduced and included in the models instead of reliability measures using statistical terms. Surprisingly, these variables had positive coefficient which suggests the presence of inertia and unwillingness to change their lane.

In order to eliminate the impact of the panel data and unobserved factors that are the same over time for a particular traveler, one trip for each traveler was selected to be included in the models. Different models were developed using different reliability measures. Models including toll, time and reliability had a positive coefficient for at least one of these variables for one period of time. There were two measures of reliability (travel time index and planning time index) that led to negative coefficients for time and reliability when ASC, time and reliability were only included in the models. This suggests that travelers may not care about the exact amount of toll; the fact that they have to pay a toll is what mainly impacts their decisions. However, when mixed logit models were developed to account for the random taste variation across travelers, the range of the coefficient for time or reliability in such models (with ASC, time and reliability as independent variables) included positive numbers for at least one of the time periods. So, this conclusion was no longer valid.

When only time and toll were included in the multinomial logit models, reasonable VOTs were obtained. However, developing mixed logit models with the same variables led to a positive mean coefficient for time.

Among multinomial logit models, there were 10 models with time, reliability and toll as independent variables that had negative coefficients for these variables when dataset included all time periods (peak period, shoulder period, and off peak period) and was not limited to one period of time. These models had positive coefficient for one of the variables when data was for one specific period of time. The reason might be the greater variety of toll rate, travel time saving and reliability improvement when all time periods are included in the dataset which helps the model to better capture the VOT and VOR. Table 51 shows the VOTs and VORs obtained from these models.

R^2_{McF} in Table 51, is a likelihood ratio index that is analogous to the R-square in the linear regression model (except that values of R^2_{McF} around 0.3 or better are considered as acceptable or even good, which they would often not be in the R^2 case):

$$R^2_{McF} = 1 - \frac{Ln L}{Ln L_0} \quad (27)$$

Where L is the maximum of the log-likelihood function and L_0 is the maximum of the log-likelihood function when all coefficients are zero. McFadden's likelihood ratio index is bounded by 0 and 1. If a model has a low likelihood, then the log of the likelihood is large. Thus, a smaller ratio of log likelihoods (larger R^2_{McF}) indicates a better model.

Table 51 VOT and VOR Obtained from Intuitive Logit Models

Variable	Coefficient	VOT	VOR	Correct Estimations	R ² _{McF} *	Consideration
Model: $U_{TOLL}=B_1\times time+B_2\times SD+B_3\times toll$, $U_{GPL}=B_1\times time+B_2\times SD+B_3\times toll$						
Time	-0.19	\$5.51/hr	\$6.37/hr	91%	0.263	Standard deviation (SD) of time and time are highly correlated.
SD	-0.22					
Toll	-2.07					
Model: $U_{TOLL}=B_1\times time+B_2\times 95th+B_3\times toll$, $U_{GPL}=B_1\times time+B_2\times 95th+B_3\times toll$						
Time	-0.19	\$5.38/hr	\$1.98/hr	91%	0.261	95 th percentile of time and time are highly correlated.
95 th Percentile	-0.07					
Toll	-2.12					
Model: $U_{TOLL}=B_1\times time+B_2\times IR+B_3\times toll$, $U_{GPL}=B_1\times time+B_2\times IR+B_3\times toll$						
Time	-0.11	\$2.35/hr	\$17.08/hr	89%	0.319	Interquartile range of time and time are highly correlated.
IR	-0.80					
Toll	-2.81					
Model: $U_{TOLL}=B_1\times time+B_2\times SRR+B_3\times toll$, $U_{GPL}=B_1\times time+B_2\times SRR+B_3\times toll$						
Time	-0.20	\$5.82/hr	\$2.04/hr	91%	0.259	Short right range of time and time are highly correlated.
SRR	-0.07					
Toll	-2.06					
Model: $U_{TOLL}=B_1\times time+B_2\times PT+B_3\times toll$, $U_{GPL}=B_1\times time+B_2\times PT+B_3\times toll$						
Time	-0.22	\$6.60/hr	Value of reducing unacceptable trips by 10 percent = 3.3 cents.	91%	0.257	
PT	-0.67					
Toll	-2.00					
Model: $U_{TOLL}=B_1\times time+B_2\times CV+B_3\times toll$, $U_{GPL}=B_1\times time+B_2\times CV+B_3\times toll$						
Time	-0.14	\$24.00/hr	Value of reducing coefficient of variation by 1 percent = 5.4 cents.	61%	0.030	Only trips of travelers who alternated their lane choice were included in the dataset.
CV	-1.89					
Toll	-0.35					
Model: $U_{TOLL}=B_1\times time+B_2\times MI+B_3\times toll$, $U_{GPL}=B_1\times time+B_2\times MI+B_3\times toll$						
Time	-0.15	\$23.68/hr	Value of reducing misery index by 1 percent = 4.0 cents.	62%	0.031	Only trips of travelers who alternated their lane choice were included in the dataset.
MI	-1.51					
Toll	-0.38					
Model: $U_{TOLL}=B_1\times time+B_2\times PT+B_3\times toll$, $U_{GPL}=B_1\times time+B_2\times PT+B_3\times toll$						
Time	-0.14	\$22.70/hr	Value of reducing unacceptable trips by 1 percent = 4.0 cents.	61%	0.028	Only trips of travelers who alternated their lane choice were included in the dataset.
PT	-1.49					
Toll	-0.37					

Table 51 Continued

Variable	Coefficient	VOT	VOR	Correct Estimations	R ² _{McF} *	Consideration
Model: $U_{TOLL}=B_1\times time+B_2\times MI+B_3\times toll$, $U_{GPL}=B_1\times time+B_2\times MI+B_3\times toll$						
Time	−0.29	\$7.66/hr	Value of reducing misery index by 10 percent = 0.44 cents.	91%	0.268	Only the last trips of travelers with more than 5 trips were included in the dataset.
MI	−0.10					
Toll	−2.27					
Model: $U_{TOLL}=B_1\times time+B_2\times PT+B_3\times toll$, $U_{GPL}=B_1\times time+B_2\times PT+B_3\times toll$						
Time	−0.28	\$7.17/hr	Value of reducing unacceptable trips by 1 percent = 0.7 cents.	91%	0.270	Only the last trips of travelers with more than 5 trips were included in the dataset.
PT	−1.64					
Toll	−2.34					

* R^2_{McF} is "McFadden's likelihood-ratio index".

To calculate the percent of correct estimations, the probability of MLs and GPLs usage were calculated for each trip based on the models (utility functions). The lane with higher probability (probability larger than 0.5) was the predicted lane. Then, the percent of correct estimations (when the predicted lane matches the chosen lane) was calculated.

Table 51 shows that all models, except those that only model travel behavior of travelers who alternated their lane choice, have a reasonable likelihood ratio index. Previously, it was also found that excluding travelers who do not change their lane makes dataset biased and is not appropriate (see section 4.4). Besides, again except those models that only model travel behavior of travelers who alternated their lane choice, models have a high percent of correct estimation (about 90%); this shows that models are successful in predicting travelers' behavior.

In order to understand the value of reliability obtained by models with different reliability measures and be able to compare them, the average value of reliability offered by the 12 mile section of the MLs in peak period was calculated for each model (see Table 52). It can be seen that the range of the value of reliability offered by the 12 mile section of the MLs is wide, ranging from 0.09 cents to 56.00 cents. Moreover, even when VORs obtained from different reliability measures have the same unit (for example \$/hr), they cannot be compared directly. In Table 52, VOR obtained from the model with standard deviation (SD) as reliability measure seems to be larger than the VOR obtained from the model with 95th percentile of time as reliability measure. However, when value of reliability offered by MLs is calculated the latter suggests a larger value. Overall, it can be concluded that results from different reliability measures are different and a definitive measure is needed. However, the results from this research fail to suggest a definitive measure as the models included in Tables 50 and 51 yield to positive coefficient for either time, reliability or toll when dataset is limited to one time period. Moreover, when the mixed logit models were developed, none of the models had negative mean coefficient for time, toll, and reliability, even for the case that data from all time periods were combined in the dataset.

Table 52 Average Value of Reliability Offered by MLs in Peak Period

Variable	Coefficient	VOT	VOR	MLs Reliability	GPLs Reliability	Value of Reliability Offered by MLs
Model: $U_{TOLL}=B_1\times time+B_2\times SD+B_3\times toll$, $U_{GPL}=B_1\times time+B_2\times SD+B_3\times toll$						
Time	-0.19	\$5.51/hr	\$6.37/hr	4.24 min	7.01 min	29.41 cents
SD	-0.22					
Toll	-2.07					
Model: $U_{TOLL}=B_1\times time+B_2\times 95th+B_3\times toll$, $U_{GPL}=B_1\times time+B_2\times 95th+B_3\times toll$						
Time	-0.19	\$5.38/hr	\$1.98/hr	22.40 min	33.23 min	35.74 cents
95 th Percentile	-0.07					
Toll	-2.12					
Model: $U_{TOLL}=B_1\times time+B_2\times IR+B_3\times toll$, $U_{GPL}=B_1\times time+B_2\times IR+B_3\times toll$						
Time	-0.11	\$2.35/hr	\$17.08/hr	2.89 min	4.84 min	55.51 cents
IR	-0.80					
Toll	-2.81					
Model: $U_{TOLL}=B_1\times time+B_2\times SRR+B_3\times toll$, $U_{GPL}=B_1\times time+B_2\times SRR+B_3\times toll$						
Time	-0.20	\$5.82/hr	\$2.04/hr	10.25 min	15.26 min	17.03 cents
SRR	-0.07					
Toll	-2.06					
Model: $U_{TOLL}=B_1\times time+B_2\times PT+B_3\times toll$, $U_{GPL}=B_1\times time+B_2\times PT+B_3\times toll$						
Time	-0.22	\$6.60/hr	Value of reducing unacceptable trips by 10 percent = 3.35 cents.	16.7%	30.8%	4.72 cents
PT	-0.67					
Toll	-2.00					
Model: $U_{TOLL}=B_1\times time+B_2\times CV+B_3\times toll$, $U_{GPL}=B_1\times time+B_2\times CV+B_3\times toll^*$						
Time	-0.14	\$24.00/hr	Value of reducing coefficient of variation by 1 percent = 5.4 cents.	26.6%	32.1%	29.70 cents
CV	-1.89					
Toll	-0.35					
Model: $U_{TOLL}=B_1\times time+B_2\times MI+B_3\times toll$, $U_{GPL}=B_1\times time+B_2\times MI+B_3\times toll^*$						
Time	-0.15	\$23.68/hr	Value of reducing misery index by 1 percent = 4.0 cents.	38.6%	48.5%	39.60 cents
MI	-1.51					
Toll	-0.38					
Model: $U_{TOLL}=B_1\times time+B_2\times PT+B_3\times toll$, $U_{GPL}=B_1\times time+B_2\times PT+B_3\times toll^*$						
Time	-0.14	\$22.70/hr	Value of reducing unacceptable trips by 1 percent = 4.0 cents.	17.0%	31.0%	56.00 cents
PT	-1.49					
Toll	-0.37					

Table 52 Continued

Variable	Coefficient	VOT	VOR	MLs Reliability	GPLs Reliability	Value of Reliability Offered by MLs
Model: $U_{TOLL}=B_1\times time+B_2\times MI+B_3\times toll$, $U_{GPL}=B_1\times time+B_2\times MI+B_3\times toll^{**}$						
Time	-0.29	\$7.66/hr	Value of reducing misery index by 1 percent = 4.0 cents.	44.0%	46.0%	0.09 cents
MI	-0.10					
Toll	-2.27					
Model: $U_{TOLL}=B_1\times time+B_2\times PT+B_3\times toll$, $U_{GPL}=B_1\times time+B_2\times PT+B_3\times toll^{**}$						
Time	-0.28	\$7.17/hr	Value of reducing unacceptable trips by 1 percent = 4.0 cents.	13.2%	30.2%	11.90 cents
PT	-1.64					
Toll	-2.34					

* Only those travelers who alternated their lane choice were included.

** Only the last trips of travelers with more than 5 trips were included in the dataset.

5. CONCLUSION AND RECOMMENDATIONS

The objective of this research was to find the best measure of reliability and the value of reliability by studying travel behavior and lane choice of Katy Freeway travelers. Multinomial logit models and mixed logit models were used to understand how trip attributes including travel time, toll, and travel time reliability impact travelers' choice between the GPLs and MLs.

It was found that most of the trips on the MLs occurred during the peak hours when MLs offer greater travel time savings and better reliability, but when the toll is highest. This suggests that travel time savings and reliability improvement influences traveler's lane choice. However, about 78 percent of travelers who had more than five trips during the study period (April 2012) never changed their lane of choice. 99 percent of those travelers, who never changed their lane, always used GPLs and 1 percent always used the MLs.

Several models with different measures of reliability were developed in an attempt to explain travelers' lane choice behavior. However, all models failed to explain travelers' behavior on the freeway as they had positive coefficients for at least one of the trip attributes for one the time periods (travel time, unreliability and toll), suggesting an increase in travel time, unreliability or toll increases the travelers' utility of using the lane. This is clearly contrary to the way travelers decide based on these attributes. Different approaches were used in an attempt to overcome this issue. In one attempt, travelers who never changed their lane were excluded from datasets. However, this

approach yielded unreasonably high VOTs and it biased the dataset in favor of MLs usage. In another attempt, instead of reliability measures, dummy variables, which show whether the traveler had a bad trip experience on a lane set, were used in the model. Surprisingly, these dummy variables had a positive coefficient, suggesting many travelers do not change their lane even though they experienced a bad trip on that lane. This can be explained by the large number of travelers who never changed their lane choice and have a predefined approach toward MLs. Therefore, it can be concluded that inertia of behavior or unwillingness to change the lane has a significant impact on travelers' lane choice.

Reasonable VOTs were obtained using multinomial logit models when only time and toll were included in the model. However, the addition of an ACS to the model led to a positive coefficient for the toll and relatively large ASC values. This implies that there was a weak relationship between lane choice and trip attributes as used in the model. When a mixed logit model was used, with only time and toll included in the model, time got a positive mean coefficient. Since the distribution for the coefficient of time includes negative numbers, the results from the mixed logit models and multinomial logit models are not contradictory. However, the results from the mixed logit models suggest that there is heterogeneity across travelers, as standard deviation of time coefficient is larger than zero, and mixed logit models should be used to account for the heterogeneity. Therefore, considering the result from mixed logit models, it was not possible to obtain reasonable VOTs because the mean coefficients of time in mixed logit models were positive.

When reliability measures were added to the models, models with time, toll and reliability as independent variables had a positive coefficient for either time, toll or reliability for at least one of the time periods. Therefore, it was impossible to extract VORs from the models since models were considered to be counter-intuitive. However, to see how different reliability measures can lead to different results, VORs were obtained from the models that had negative coefficients for time, toll and reliability when all time periods were included in the dataset. The range of average value of reliability offered by MLs during the peak period was found to be from 0.09 cents to 56.00 cents suggesting that a definitive reliability measure is certainly needed.

When ASC, time and reliability were only included in the models, there were two measures of reliability (travel time index and planning time index) that led to negative coefficients for time and reliability. This suggests that travelers may not care about the exact amount of toll, but the fact that they have to pay a toll is what mainly impacts their decisions. However, when mixed logit models were developed to account for the random taste variation across travelers, the range of the coefficients for time or reliability in such models (with ASC, time and reliability as independent variables) included positive numbers for at least one of time periods. Therefore, such a conclusion is not logical.

The fact that models failed to provide intuitive results may be due to several reasons. One reason could be the lack of sufficient variation in the toll schedule. Another limitation is the lack of travelers' characteristic information. Also, other attributes of GPLs and MLs such as accessibility, which were not included in the models, may have influences on travelers' decisions. There is also a chance that travelers' perception of the

benefit of MLs is not limited to travel time saving and travel time reliability since it can be seen that even during the off peak period, when travel time saving is very small, some travelers use MLs. Moreover, travelers' perception of travel time reliability might be different from all measures that were used in this research.

The most noticeable issue about the data is the large number of travelers who always use the GPLs. The VOT and VOR for this group of travelers must be studied. There is a chance that VOT and VOR for this group of travelers are too low to be captured by the small travel time saving and reliability improvement offered by MLs. It would be good to conduct a survey and, instead of providing respondents with options of noticeable travel time and travel time reliability differences, ask respondents about the amount of time they think they would save if they use MLs, and about the range of their travel time on GPLs and MLs to see how their estimation is different from reality. Discrete choice models can also be developed based on travelers' estimation of travel time savings, reliability improvement and lane choice. Additionally, travelers should be asked about any reason that might impact their lane choice decision. In case accessibly, safety and comfort were found to impact their lane choice, those variables should be included in the model as well.

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APPENDIX

A table with all trip attributes of actual trips and alternative trips is needed to be able to run this code (see Table 3).

```
/*Deleting weekend and holidays data */
Data code.tripw;
    set code.trips;
    date = datepart (starttime);
    weekday = weekday (date);
    if weekday ne 1 and weekday ne 7;
if date=19089 then delete;
run;

/*travel time per mile*/
data code.final;
set code.tripw;
    timel=time/length;
run;

/*adding reliability measures*/
data code.final;
set code.final;
min=minute(starttime);
hour=hour(starttime);
if hour=0 then cat=1;
if hour=1 then cat=1;
if hour=2 then cat=1;
if hour=3 then cat=1;
if hour=4 then cat=1;
if hour=5 then cat=1;
if hour=6 and 0=<min<30 and peak2=1 then cat=2;
if hour=6 and 30=<min<60 and peak2=1 then cat=3;
if hour=7 and 0=<min<30 and peak2=1 then cat=4;
if hour=7 and 30=<min<60 and peak2=1 then cat=5;
if hour=8 and 0=<min<30 and peak2=1 then cat=6;
if hour=8 and 30=<min<60 and peak2=1 then cat=7;
if hour=9 and 0=<min<30 and peak2 =1 then cat=8;
if hour=9 and 30=<min<60 and peak2=1 then cat=9;
if hour=10 then cat=10;
if hour=11 then cat=11;
if hour=12 then cat=12;
if hour=13 then cat=13;
if hour=14 then cat=14;
if hour=15 and 0=<min<30 and peak2=1 then cat=15;
if hour=15 and 30=<min<60 and peak2=1 then cat=16;
if hour=16 and 0=<min<30 and peak2=1 then cat=17;
if hour=16 and 30=<min<60 and peak2=1 then cat=18;
if hour=17 and 0=<min<30 and peak2=1 then cat=19;
```

```

if hour=17 and 30=<min<60 and peak2=1 then cat=20;
if hour=18 and 0=<min<30 and peak2=1 then cat=21;
if hour=18 and 30=<min<60 and peak2=1 then cat=22;
if hour=19 then cat=23;
if hour=20 then cat=24;
if hour=21 then cat=25;
if hour=22 then cat=26;
if hour=23 then cat=27;
if hour=6 and peak2=0 then cat=28;
if hour=7 and peak2=0 then cat=29;
if hour=8 and peak2=0 then cat=30;
if hour=9 and peak2=0 then cat=31;
if hour=15 and peak2=0 then cat=32;
if hour=16 and peak2=0 then cat=33;
if hour=17 and peak2=0 then cat=34;
if hour=18 and peak2=0 then cat=35;
run;
data code.final1;
set code.final;
if lanechoice=1;
run;
proc univariate data=code.final1 noprint;
var timel;
output out=code.percentile pctlpts= 50 75 25 80 90 95 pctlpre=p std=S
mean=Ave ;
class cat mldum;
run;
proc sort data= code.final;
by cat mldum;
run;
proc sort data= code.percentile;
by cat mldum;
run;
data code.final2;
merge code.final code.percentile;
by cat mldum;
run;
data code.final2;
set code.final2;
mean=ave*length;
stdd=s*length;
t50=p50*length;
t75=p75*length;
t80=p80*length;
t90=p90*length;
t95=p95*length;
t25=P25*length;
run;
data code.final2;
set code.final2;
x=1;
y=0;
if time>t50*1.2 then y=1;
run;

```

```

Proc sql noprint;
    Create Table code.sum
    as select obs,cat, mldum, sum(x) as sumx, sum(y) as sumy
    from code.final2
    group by cat, mldum;
quit;
data code.sum;
set code.sum;
pt=sumy/sumx;
drop sumy sumx cat;
run;
proc sort data=code.final2;
by obs;
run;
proc sort data=code.sum;
by obs;
run;
data code.final3;
merge code.final2 code.sum;
by obs mldum;
run;
data code.final4;
set code.final3;
if time>t80;
run;
Proc sql noprint;
    Create Table code.final5
    as select cat, mldum, mean(timel) as ave800
    from code.final4
    group by cat, mldum;
quit;
proc sort data= code.final3;
by cat mldum;
run;
proc sort data= code.final5;
by cat mldum;
run;
data code.final6;
merge code.final3 code.final5;
by cat mldum;
run;
proc sort data= code.final6;
by obs;
run;
data code.month;
set code.final6;
drop x y;
fft=0.857142857*length;
tti=mean/fft;
bti=(t95-mean)/mean;
pti=t95/fft;
cv=stdd/mean;
srr=t95-t50;
ir=t75-t25;

```

```

        ave80=ave800*length;
        MI= (ave80-mean)/mean;
    run;
data code.peak;
set code.month;
if peak1=1;
run;
    data code.shoulder;
set code.month;
if peak1=0 and peak2=1;
run;
    data code.offpeak;
set code.month;
if peak1=0 and peak2=0;
run;
/*logit models*/
proc mdc data=code.month;
    model lanechoice = time totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.month;
    model lanechoice = mldum time totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.peak;
    model lanechoice = time totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.peak;
    model lanechoice = mldum time totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.shoulder;
    model lanechoice = time totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.shoulder;
    model lanechoice = mldum time totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.offpeak;
    model lanechoice = time totaltoll/

```

```

        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.offpeak;
    model lanechoice = mldum time totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.month;
    model lanechoice = mldum time stdd totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.month;
    model lanechoice = time stdd totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.month;
    model lanechoice = mldum time stdd/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.peak;
    model lanechoice = mldum time stdd totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.peak;
    model lanechoice = time stdd totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.peak;
    model lanechoice = mldum time stdd/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.shoulder;
    model lanechoice = mldum time stdd totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.shoulder;
    model lanechoice = time stdd totaltoll/

```

```

        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.shoulder;
    model lanechoice = mldum time stdd/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.offpeak;
    model lanechoice = mldum time stdd totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.offpeak;
    model lanechoice = time stdd totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.offpeak;
    model lanechoice = mldum time stdd/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.month;
    model lanechoice = mldum time t95 totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.month;
    model lanechoice = time t95 totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.month;
    model lanechoice = mldum time t95/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.peak;
    model lanechoice = mldum time t95 totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.peak;
    model lanechoice = time t95 totaltoll/

```

```

        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.peak;
    model lanechoice = mldum time t95/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.shoulder;
    model lanechoice = mldum time t95 totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.shoulder;
    model lanechoice = time t95 totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.shoulder;
    model lanechoice = mldum time t95/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.offpeak;
    model lanechoice = mldum time t95 totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.offpeak;
    model lanechoice = time t95 totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.offpeak;
    model lanechoice = mldum time t95/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.month;
    model lanechoice = mldum time ir totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.month;
    model lanechoice = time ir totaltoll/

```



```

        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.month;
    model lanechoice = mldum time ir/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.peak;
    model lanechoice = mldum time ir totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.peak;
    model lanechoice = time ir totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.peak;
    model lanechoice = mldum time ir/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.shoulder;
    model lanechoice = mldum time ir totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.shoulder;
    model lanechoice = time ir totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.shoulder;
    model lanechoice = mldum time ir/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.offpeak;
    model lanechoice = mldum time ir totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.offpeak;
    model lanechoice = time ir totaltoll/

```

```

        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.offpeak;
    model lanechoice = mldum time ir/
        type=clogit
        nchoice=2;
    id id;
run;

proc mdc data=code.month;
    model lanechoice = mldum time srr totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.month;
    model lanechoice = time srr totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.month;
    model lanechoice = mldum time srr/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.peak;
    model lanechoice = mldum time srr totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.peak;
    model lanechoice = time srr totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.peak;
    model lanechoice = mldum time srr/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.shoulder;
    model lanechoice = mldum time srr totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.shoulder;

```

```

        model lanechoice = time srr totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.shoulder;
    model lanechoice = mldum time srr/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak;
    model lanechoice = mldum time srr totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak;
    model lanechoice = time srr totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak;
    model lanechoice = mldum time srr/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.month;
    model lanechoice = mldum time tti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.month;
    model lanechoice = time tti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.month;
    model lanechoice = mldum time tti/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.peak;
    model lanechoice = mldum time tti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.peak;

```

```

        model lanechoice = time tti totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.peak;
    model lanechoice = mldum time tti/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.shoulder;
    model lanechoice = mldum time tti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.shoulder;
    model lanechoice = time tti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.shoulder;
    model lanechoice = mldum time tti/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak;
    model lanechoice = mldum time tti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak;
    model lanechoice = time tti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak;
    model lanechoice = mldum time tti/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.month;
    model lanechoice = mldum time bti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.month;

```

```

        model lanechoice = time bti totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.month;
    model lanechoice = mldum time bti/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.peak;
    model lanechoice = mldum time bti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.peak;
    model lanechoice = time bti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.peak;
    model lanechoice = mldum time bti/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.shoulder;
    model lanechoice = mldum time bti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.shoulder;
    model lanechoice = time bti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.shoulder;
    model lanechoice = mldum time bti/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak;
    model lanechoice = mldum time bti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak;

```

```

        model lanechoice = time bti totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.offpeak;
    model lanechoice = mldum time bti/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.month;
    model lanechoice = mldum time pti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.month;
    model lanechoice = time pti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.month;
    model lanechoice = mldum time pti/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.peak;
    model lanechoice = mldum time pti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.peak;
    model lanechoice = time pti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.peak;
    model lanechoice = mldum time pti/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.shoulder;
    model lanechoice = mldum time pti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.shoulder;

```

```

        model lanechoice = time pti totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.shoulder;
    model lanechoice = mldum time pti/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak;
    model lanechoice = mldum time pti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak;
    model lanechoice = time pti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak;
    model lanechoice = mldum time pti/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.month;
    model lanechoice = mldum time mi totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.month;
    model lanechoice = time mi totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.month;
    model lanechoice = mldum time mi/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.peak;
    model lanechoice = mldum time mi totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.peak;

```

```

        model lanechoice = time mi totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.peak;
    model lanechoice = mldum time mi/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.shoulder;
    model lanechoice = mldum time mi totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.shoulder;
    model lanechoice = time mi totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.shoulder;
    model lanechoice = mldum time mi/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak;
    model lanechoice = mldum time mi totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak;
    model lanechoice = time mi totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak;
    model lanechoice = mldum time mi/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.month;
    model lanechoice = mldum time pt totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.month;

```



```

        model lanechoice = time pt totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.month;
    model lanechoice = mldum time pt/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.peak;
    model lanechoice = mldum time pt totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.peak;
    model lanechoice = time pt totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.peak;
    model lanechoice = mldum time pt/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.shoulder;
    model lanechoice = mldum time pt totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.shoulder;
    model lanechoice = time pt totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.shoulder;
    model lanechoice = mldum time pt/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak;
    model lanechoice = mldum time pt totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak;

```

```

        model lanechoice = time pt totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.offpeak;
    model lanechoice = mldum time pt/
    type=clogit
    nchoice=2;
    id id;
run;

/*excluding travelers that do not make a decision */
Data code.trips1;
    set code.month;
    if totaltrips=<5 then delete;
    ml=mldum*lanechoice;
run;
proc sql noprint;
    Create Table code.trips2 as select obs, randid, totaltrips,
sum(ml) as summl from code.trips1 group by randid;
quit;
proc sort data=code.trips2;
    by obs;
run;
proc sort data=code.trips1;
    by obs;
run;
Data code.trips2;
    set code.trips2;
    drop randid totaltrips;
run;
Data code.trips3;
    merge code.trips2 code.trips1 ;
    by obs;
run;

Data code.finalmonth;
    set code.trips3;
    if summl=totaltrips or summl=0 then delete;
run;
Data code.peak1;
set code.finalmonth;
    if peak1=1;
run;
Data code.shoulder1;
set code.finalmonth;
    if peak1=0 and peak2=1;
run;
Data code.offpeak1;
set code.finalmonth;
    if peak1=0 and peak2=0;
run;
proc mdc data=code.finalmonth;

```

```

        model lanechoice = mldum time cv totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.finalmonth;
    model lanechoice = time cv totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.finalmonth;
    model lanechoice = mldum time cv/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.peak1;
    model lanechoice = mldum time cv totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.peak1;
    model lanechoice = time cv totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.peak1;
    model lanechoice = mldum time cv/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.shoulder1;
    model lanechoice = mldum time cv totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.shoulder1;
    model lanechoice = time cv totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.shoulder1;
    model lanechoice = mldum time cv/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak1;

```

```

        model lanechoice = mldum time cv totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.offpeak1;
    model lanechoice = time cv totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak1;
    model lanechoice = mldum time cv/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.finalmonth;
    model lanechoice = mldum time tti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.finalmonth;
    model lanechoice = time tti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.finalmonth;
    model lanechoice = mldum time tti/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.peak1;
    model lanechoice = mldum time tti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.peak1;
    model lanechoice = time tti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.peak1;
    model lanechoice = mldum time tti/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.shoulder1;

```

```

        model lanechoice = mldum time tti totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.shoulder1;
    model lanechoice = time tti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.shoulder1;
    model lanechoice = mldum time tti/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak1;
    model lanechoice = mldum time tti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak1;
    model lanechoice = time tti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak1;
    model lanechoice = mldum time tti/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.finalmonth;
    model lanechoice = mldum time bti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.finalmonth;
    model lanechoice = time bti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.finalmonth;
    model lanechoice = mldum time bti/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.peak1;

```

```

        model lanechoice = mldum time bti totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.peak1;
    model lanechoice = time bti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.peak1;
    model lanechoice = mldum time bti/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.shoulder1;
    model lanechoice = mldum time bti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.shoulder1;
    model lanechoice = time bti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.shoulder1;
    model lanechoice = mldum time bti/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak1;
    model lanechoice = mldum time bti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak1;
    model lanechoice = time bti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak1;
    model lanechoice = mldum time bti/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.finalmonth;

```

```

        model lanechoice = mldum time pti totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.finalmonth;
    model lanechoice = time pti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.finalmonth;
    model lanechoice = mldum time pti/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.peak1;
    model lanechoice = mldum time pti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.peak1;
    model lanechoice = time pti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.peak1;
    model lanechoice = mldum time pti/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.shoulder1;
    model lanechoice = mldum time pti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.shoulder1;
    model lanechoice = time pti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.shoulder1;
    model lanechoice = mldum time pti/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak1;

```

```

        model lanechoice = mldum time pti totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.offpeak1;
    model lanechoice = time pti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak1;
    model lanechoice = mldum time pti/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.finalmonth;
    model lanechoice = mldum time mi totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.finalmonth;
    model lanechoice = time mi totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.finalmonth;
    model lanechoice = mldum time mi/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.peak1;
    model lanechoice = mldum time mi totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.peak1;
    model lanechoice = time mi totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.peak1;
    model lanechoice = mldum time mi/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.shoulder1;

```



```

        model lanechoice = mldum time mi totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.shoulder1;
    model lanechoice = time mi totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.shoulder1;
    model lanechoice = mldum time mi/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak1;
    model lanechoice = mldum time mi totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak1;
    model lanechoice = time mi totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak1;
    model lanechoice = mldum time mi/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.finalmonth;
    model lanechoice = mldum time pt totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.finalmonth;
    model lanechoice = time pt totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.finalmonth;
    model lanechoice = mldum time pt/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.peak1;

```

```

        model lanechoice = mldum time pt totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.peak1;
    model lanechoice = time pt totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.peak1;
    model lanechoice = mldum time pt/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.shoulder1;
    model lanechoice = mldum time pt totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.shoulder1;
    model lanechoice = time pt totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.shoulder1;
    model lanechoice = mldum time pt/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak1;
    model lanechoice = mldum time pt totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak1;
    model lanechoice = time pt totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak1;
    model lanechoice = mldum time pt/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.finalmonth;

```

```

        model lanechoice = time totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.finalmonth;
    model lanechoice = mldum time totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.peak1;
    model lanechoice = time totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.peak1;
    model lanechoice = mldum time totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.shoulder1;
    model lanechoice = time totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.shoulder1;
    model lanechoice = mldum time totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak1;
    model lanechoice = time totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak1;
    model lanechoice = mldum time totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
/*last-bad trip experience, unacceptable trip= triptime>t80 */
Data code.trip1;
    set code.month;
    bad=0;
    if time>t80 then bad=1;
run;
Data code.trip2;

```

```

        set code.trip1;
        if gpldum=1;
            laglane=lag(lanechoice);
            lagbad=lag(bad);
            laded=lag(randid);
            lti=0;
            if laglane=1 and laded=randid and lagbad=1 then lti=1;
        run;

Data code.trip3;
    set code.trip1;
    if mldum=1;
        laglane=lag(lanechoice);
        lagbad=lag(bad);
        laded=lag(randid);
        lti=0;
        if laglane=1 and laded=randid and lagbad=1 then lti=1;
    run;

Data code.trip22;
    set code.trip2;
retain inter;
x=0;
bte=0;
if randid ne lag(randid) then
    do;
        inter=LTI;
    end;
if randid=lag(randid) then
    do;
        x =(inter+lti);
        inter=x;
    end;
drop inter;
if x>0 then bte=1;
run;

Data code.trip33;
set code.trip3;
retain inter;
x=0;
bte=0;
if randid ne lag(randid) then
    do;
        inter=LTI;
    end;
if randid=lag(randid) then
    do;
        x =(inter+lti);
        inter=x;
    end;
drop inter;
if x>0 then bte=1;
run;
Data code.finalmonth2;

```

```

        set code.trip22 last.trip22;
    run;
proc sort data=code.finalmonth2;
    by obs;
run;
Data code.peak2;
    set code.finalmonth2;
    if peak1=1;
    run;
Data code.shoulder2;
    set code.finalmonth2;
    if peak1=0 and peak2=1;
    run;
Data code.offpeak2;
    set code.finalmonth2;
    if peak1=0 and peak2=0;
    run;
proc mdc data=code.finalmonth2;
    model lanechoice = mldum time lti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.finalmonth2;
    model lanechoice = time lti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.finalmonth2;
    model lanechoice = mldum time lti/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.peak2;
    model lanechoice = mldum time lti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.peak2;
    model lanechoice = time lti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.peak2;
    model lanechoice = mldum time lti/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.shoulder2;

```

```

        model lanechoice = mldum time lti totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.shoulder2;
    model lanechoice = time lti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.shoulder2;
    model lanechoice = mldum time lti/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak2;
    model lanechoice = mldum time lti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak2;
    model lanechoice = time lti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak2;
    model lanechoice = mldum time lti/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.finalmonth2;
    model lanechoice = mldum time bte/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.peak2;
    model lanechoice = mldum time bte totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.peak2;
    model lanechoice = time bte totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.peak2;

```

```

        model lanechoice = mldum time bte/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.shoulder2;
    model lanechoice = mldum time bte totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.shoulder2;
    model lanechoice = time bte totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.shoulder2;
    model lanechoice = mldum time bte/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak2;
    model lanechoice = mldum time bte totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak2;
    model lanechoice = time bte totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak2;
    model lanechoice = mldum time bte/
    type=clogit
    nchoice=2;
    id id;
run;
/*last-bad trip experience, unacceptable trip= triptime>1.4*t50 */
Data code.trip1;
    set code.month;
    bad=0;
    if time>1.4*t50 then bad=1;
run;
Data code.trip2;
    set code.trip1;
    if gpldum=1;
    laglane=lag(lanechoice);
    lagbad=lag(bad);
    ladiid=lag(randid);
    lti=0;

```

```

        if laglane=1 and laded=randid and lagbad=1 then lti=1;
        run;

Data code.trip3;
    set code.trip1;
    if mldum=1;
        laglane=lag(lanechoice);
        lagbad=lag(bad);
        laded=lag(randid);
        lti=0;
        if laglane=1 and laded=randid and lagbad=1 then lti=1;
        run;

Data code.trip22;
    set code.trip2;
retain inter;
x=0;
bte=0;
if randid ne lag(randid) then
    do;
        inter=LTI;
    end;
if randid=lag(randid) then
    do;
        x =(inter+lti);
        inter=x;
    end;
drop inter;
if x>0 then bte=1;
run;

Data code.trip33;
set code.trip3;
retain inter;
x=0;
bte=0;
if randid ne lag(randid) then
    do;
        inter=LTI;
    end;
if randid=lag(randid) then
    do;
        x =(inter+lti);
        inter=x;
    end;
drop inter;
if x>0 then bte=1;
run;

Data code.finalmonth2;
    set code.trip22 last.trip22;
    run;
proc sort data=code.finalmonth2;
    by obs;
run;
Data code.peak2;

```



```

        set code.finalmonth2;
        if peak1=1;
        run;
Data code.shoulder2;
    set code.finalmonth2;
    if peak1=0 and peak2=1;
    run;
Data code.offpeak2;
    set code.finalmonth2;
    if peak1=0 and peak2=0;
    run;
proc mdc data=code.finalmonth2;
    model lanechoice = mldum time lti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.finalmonth2;
    model lanechoice = time lti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.finalmonth2;
    model lanechoice = mldum time lti/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.peak2;
    model lanechoice = mldum time lti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.peak2;
    model lanechoice = time lti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.peak2;
    model lanechoice = mldum time lti/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.shoulder2;
    model lanechoice = mldum time lti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.shoulder2;

```

```

        model lanechoice = time lti totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.shoulder2;
    model lanechoice = mldum time lti/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak2;
    model lanechoice = mldum time lti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak2;
    model lanechoice = time lti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak2;
    model lanechoice = mldum time lti/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.finalmonth2;
    model lanechoice = mldum time bte/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.peak2;
    model lanechoice = mldum time bte totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.peak2;
    model lanechoice = time bte totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.peak2;
    model lanechoice = mldum time bte/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.shoulder2;

```

```

        model lanechoice = mldum time bte totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.shoulder2;
    model lanechoice = time bte totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.shoulder2;
    model lanechoice = mldum time bte/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak2;
    model lanechoice = mldum time bte totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak2;
    model lanechoice = time bte totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak2;
    model lanechoice = mldum time bte/
    type=clogit
    nchoice=2;
    id id;
run;
/*last-bad trip experience, unacceptable trip= triptime>2*t50 */
Data code.trip1;
    set code.month;
    bad=0;
    if time>2*t50 then bad=1;
run;
Data code.trip2;
    set code.trip1;
    if gpldum=1;
    laglane=lag(lanechoice);
    lagbad=lag(bad);
    ladiid=lag(randid);
    lti=0;
    if laglane=1 and ladiid=randid and lagbad=1 then lti=1;
run;

Data code.trip3;
    set code.trip1;
    if mldum=1;

```

```

        laglane=lag(lanechoice);
        lagbad=lag(bad);
        ladedid=lag(randid);
        lti=0;
        if laglane=1 and ladedid=randid and lagbad=1 then lti=1;
    run;
Data code.trip22;
    set code.trip2;
retain inter;
x=0;
bte=0;
if randid ne lag(randid) then
    do;
        inter=LTI;
    end;
if randid=lag(randid) then
    do;
        x =(inter+lti);
        inter=x;
    end;
drop inter;
if x>0 then bte=1;
run;

Data code.trip33;
set code.trip3;
retain inter;
x=0;
bte=0;
if randid ne lag(randid) then
    do;
        inter=LTI;
    end;
if randid=lag(randid) then
    do;
        x =(inter+lti);
        inter=x;
    end;
drop inter;
if x>0 then bte=1;
run;
Data code.finalmonth2;
    set code.trip22 last.trip22;
    run;
proc sort data=code.finalmonth2;
    by obs;
run;
Data code.peak2;
    set code.finalmonth2;
    if peak1=1;
    run;
Data code.shoulder2;
    set code.finalmonth2;
    if peak1=0 and peak2=1;

```

```

run;
Data code.offpeak2;
    set code.finalmonth2;
    if peak1=0 and peak2=0;
run;
proc mdc data=code.finalmonth2;
    model lanechoice = mldum time lti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.finalmonth2;
    model lanechoice = time lti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.finalmonth2;
    model lanechoice = mldum time lti/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.peak2;
    model lanechoice = mldum time lti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.peak2;
    model lanechoice = time lti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.peak2;
    model lanechoice = mldum time lti/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.shoulder2;
    model lanechoice = mldum time lti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.shoulder2;
    model lanechoice = time lti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.shoulder2;

```

```

        model lanechoice = mldum time lti/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.offpeak2;
    model lanechoice = mldum time lti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak2;
    model lanechoice = time lti totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak2;
    model lanechoice = mldum time lti/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.finalmonth2;
    model lanechoice = mldum time bte/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.peak2;
    model lanechoice = mldum time bte totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.peak2;
    model lanechoice = time bte totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.peak2;
    model lanechoice = mldum time bte/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.shoulder2;
    model lanechoice = mldum time bte totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.shoulder2;

```

```

        model lanechoice = time bte totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.shoulder2;
    model lanechoice = mldum time bte/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak2;
    model lanechoice = mldum time bte totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak2;
    model lanechoice = time bte totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak2;
    model lanechoice = mldum time bte/
    type=clogit
    nchoice=2;
    id id;
run;
/*one trip from each traveler's trips */
Proc sort data= code.month;
    by decending obs;
run;
data code.finalmonth3;
set code.month;
lag1=lag(randid);
lag2=lag2(randid);
if randid ne lag1 or randid ne lag2;
if totaltrips>5;
run;
Proc sort data= code.finalmonth3;
    by obs;
run;
data code.peak3;
set code.finalmonth3;
if peak1=1;
run;
data code.shoulder3;
set code.finalmonth3;
if peak1=0 and peak2=1;
run;
data code.offpeak3;
set code.finalmonth3;
if peak1=0 and peak2=0;

```

```

run;
proc mdc data=code.finalmonth3;
    model lanechoice = mldum time cv totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.finalmonth3;
    model lanechoice = time cv totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.finalmonth3;
    model lanechoice = mldum time cv/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.peak3;
    model lanechoice = mldum time cv totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.peak3;
    model lanechoice = time cv totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.peak3;
    model lanechoice = mldum time cv/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.shoulder3;
    model lanechoice = mldum time cv totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.shoulder3;
    model lanechoice = time cv totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.shoulder3;
    model lanechoice = mldum time cv/
        type=clogit
        nchoice=2;
    id id;

```



```

run;
proc mdc data=code.offpeak3;
  model lanechoice = mldum time cv totaltoll/
  type=clogit
  nchoice=2;
  id id;
run;
proc mdc data=code.offpeak3;
  model lanechoice = time cv totaltoll/
  type=clogit
  nchoice=2;
  id id;
run;
proc mdc data=code.offpeak3;
  model lanechoice = mldum time cv/
  type=clogit
  nchoice=2;
  id id;
run;
proc mdc data=code.finalmonth3;
  model lanechoice = mldum time tti totaltoll/
  type=clogit
  nchoice=2;
  id id;
run;
proc mdc data=code.finalmonth3;
  model lanechoice = time tti totaltoll/
  type=clogit
  nchoice=2;
  id id;
run;
proc mdc data=code.finalmonth3;
  model lanechoice = mldum time tti/
  type=clogit
  nchoice=2;
  id id;
run;
proc mdc data=code.peak3;
  model lanechoice = mldum time tti totaltoll/
  type=clogit
  nchoice=2;
  id id;
run;
proc mdc data=code.peak3;
  model lanechoice = time tti totaltoll/
  type=clogit
  nchoice=2;
  id id;
run;
proc mdc data=code.peak3;
  model lanechoice = mldum time tti/
  type=clogit
  nchoice=2;
  id id;

```

```

run;
proc mdc data=code.shoulder3;
    model lanechoice = mldum time tti totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.shoulder3;
    model lanechoice = time tti totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.shoulder3;
    model lanechoice = mldum time tti/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.offpeak3;
    model lanechoice = mldum time tti totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.offpeak3;
    model lanechoice = time tti totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.offpeak3;
    model lanechoice = mldum time tti/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.finalmonth3;
    model lanechoice = mldum time bti totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.finalmonth3;
    model lanechoice = time bti totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.finalmonth3;
    model lanechoice = mldum time bti/
        type=clogit
        nchoice=2;
    id id;

```

```

run;
proc mdc data=code.peak3;
    model lanechoice = mldum time bti totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.peak3;
    model lanechoice = time bti totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.peak3;
    model lanechoice = mldum time bti/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.shoulder3;
    model lanechoice = mldum time bti totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.shoulder3;
    model lanechoice = time bti totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.shoulder3;
    model lanechoice = mldum time bti/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.offpeak3;
    model lanechoice = mldum time bti totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.offpeak3;
    model lanechoice = time bti totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.offpeak3;
    model lanechoice = mldum time bti/
        type=clogit
        nchoice=2;
    id id;

```

```

run;
proc mdc data=code.finalmonth3;
  model lanechoice = mldum time pti totaltoll/
    type=clogit
    nchoice=2;
  id id;
run;
proc mdc data=code.finalmonth3;
  model lanechoice = time pti totaltoll/
    type=clogit
    nchoice=2;
  id id;
run;
proc mdc data=code.finalmonth3;
  model lanechoice = mldum time pti/
    type=clogit
    nchoice=2;
  id id;
run;
proc mdc data=code.peak3;
  model lanechoice = mldum time pti totaltoll/
    type=clogit
    nchoice=2;
  id id;
run;
proc mdc data=code.peak3;
  model lanechoice = time pti totaltoll/
    type=clogit
    nchoice=2;
  id id;
run;
proc mdc data=code.peak3;
  model lanechoice = mldum time pti/
    type=clogit
    nchoice=2;
  id id;
run;
proc mdc data=code.shoulder3;
  model lanechoice = mldum time pti totaltoll/
    type=clogit
    nchoice=2;
  id id;
run;
proc mdc data=code.shoulder3;
  model lanechoice = time pti totaltoll/
    type=clogit
    nchoice=2;
  id id;
run;
proc mdc data=code.shoulder3;
  model lanechoice = mldum time pti/
    type=clogit
    nchoice=2;
  id id;

```

```

run;
proc mdc data=code.offpeak3;
  model lanechoice = mldum time pti totaltoll/
  type=clogit
  nchoice=2;
  id id;
run;
proc mdc data=code.offpeak3;
  model lanechoice = time pti totaltoll/
  type=clogit
  nchoice=2;
  id id;
run;
proc mdc data=code.offpeak3;
  model lanechoice = mldum time pti/
  type=clogit
  nchoice=2;
  id id;
run;
proc mdc data=code.finalmonth3;
  model lanechoice = mldum time mi totaltoll/
  type=clogit
  nchoice=2;
  id id;
run;
proc mdc data=code.finalmonth3;
  model lanechoice = time mi totaltoll/
  type=clogit
  nchoice=2;
  id id;
run;
proc mdc data=code.finalmonth3;
  model lanechoice = mldum time mi/
  type=clogit
  nchoice=2;
  id id;
run;
proc mdc data=code.peak3;
  model lanechoice = mldum time mi totaltoll/
  type=clogit
  nchoice=2;
  id id;
run;
proc mdc data=code.peak3;
  model lanechoice = time mi totaltoll/
  type=clogit
  nchoice=2;
  id id;
run;
proc mdc data=code.peak3;
  model lanechoice = mldum time mi/
  type=clogit
  nchoice=2;
  id id;

```

```

run;
proc mdc data=code.shoulder3;
    model lanechoice = mldum time mi totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.shoulder3;
    model lanechoice = time mi totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.shoulder3;
    model lanechoice = mldum time mi/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.offpeak3;
    model lanechoice = mldum time mi totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.offpeak3;
    model lanechoice = time mi totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.offpeak3;
    model lanechoice = mldum time mi/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.finalmonth3;
    model lanechoice = mldum time pt totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.finalmonth3;
    model lanechoice = time pt totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.finalmonth3;
    model lanechoice = mldum time pt/
        type=clogit
        nchoice=2;
    id id;

```

```

run;
proc mdc data=code.peak3;
    model lanechoice = mldum time pt totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.peak1;
    model lanechoice = time pt totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.peak3;
    model lanechoice = mldum time pt/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.shoulder3;
    model lanechoice = mldum time pt totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.shoulder3;
    model lanechoice = time pt totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.shoulder3;
    model lanechoice = mldum time pt/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak3;
    model lanechoice = mldum time pt totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak3;
    model lanechoice = time pt totaltoll/
    type=clogit
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak3;
    model lanechoice = mldum time pt/
    type=clogit
    nchoice=2;
    id id;

```

```

run;
proc mdc data=code.finalmonth3;
    model lanechoice = time totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.finalmonth3;
    model lanechoice = mldum time totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.peak3;
    model lanechoice = time totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.peak3;
    model lanechoice = mldum time totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.shoulder3;
    model lanechoice = time totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.shoulder3;
    model lanechoice = mldum time totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.offpeak3;
    model lanechoice = time totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
proc mdc data=code.offpeak3;
    model lanechoice = mldum time totaltoll/
        type=clogit
        nchoice=2;
    id id;
run;
/*mixed logit models*/
proc mdc data=code.finalmonth3;
    model lanechoice =time totaltoll/
        type=mixedlogit
        mixed=(normalparm=time)

```



```

        nchoice=2;
    id id;
run;
proc mdc data=code.finalmonth3;
    model lanechoice =mldum time totaltoll/
        type=mixedlogit
            mixed=(normalparm=time)
            mixed=(normalparm=mldum)
        nchoice=2;
    id id;
run;
proc mdc data=code.peak3;
    model lanechoice =time totaltoll/
        type=mixedlogit
            mixed=(normalparm=time)
        nchoice=2;
    id id;
run;
proc mdc data=code.peak3;
    model lanechoice =mldum time totaltoll/
        type=mixedlogit
            mixed=(normalparm=time)
            mixed=(normalparm=mldum)
        nchoice=2;
    id id;
run;
proc mdc data=code.shoulder3;
    model lanechoice =time totaltoll/
        type=mixedlogit
            mixed=(normalparm=time)
        nchoice=2;
    id id;
run;
proc mdc data=code.shoulder3;
    model lanechoice =mldum time totaltoll/
        type=mixedlogit
            mixed=(normalparm=time)
            mixed=(normalparm=mldum)
        nchoice=2;
    id id;
run;
proc mdc data=code.offpeak3;
    model lanechoice =time totaltoll/
        type=mixedlogit
            mixed=(normalparm=time)
        nchoice=2;
    id id;
run;
proc mdc data=code.offpeak3;
    model lanechoice =mldum time totaltoll/
        type=mixedlogit
            mixed=(normalparm=time)
            mixed=(normalparm=mldum)
        nchoice=2;

```

```

    id id;
run;
proc mdc data=code.finalmonth3;
    model lanechoice =mldum time cv totaltoll/
        type=mixedlogit
            mixed=(normalparm=time)
                mixed=(normalparm=cv)
                    mixed=(normalparm=mldum)
        nchoice=2;
    id id;
run;
proc mdc data=code.finalmonth3;
    model lanechoice = time cv totaltoll/
        type=mixedlogit
            mixed=(normalparm=time)
                mixed=(normalparm=cv)
        nchoice=2;
    id id;
run;
proc mdc data=code.finalmonth3;
    model lanechoice =mldum time cv/
        type=mixedlogit
            mixed=(normalparm=time)
                mixed=(normalparm=cv)
                    mixed=(normalparm=mldum)
        nchoice=2;
    id id;
run;
proc mdc data=code.peak3;
    model lanechoice =mldum time cv totaltoll/
        type=mixedlogit
            mixed=(normalparm=time)
                mixed=(normalparm=cv)
                    mixed=(normalparm=mldum)
        nchoice=2;
    id id;
run;
proc mdc data=code.peak3;
    model lanechoice = time cv totaltoll/
        type=mixedlogit
            mixed=(normalparm=time)
                mixed=(normalparm=cv)
        nchoice=2;
    id id;
run;
proc mdc data=code.peak3;
    model lanechoice =mldum time cv/
        type=mixedlogit
            mixed=(normalparm=time)
                mixed=(normalparm=cv)
                    mixed=(normalparm=mldum)
        nchoice=2;
    id id;
run;

```

```

proc mdc data=code.shoulder3;
  model lanechoice =mldum time cv totaltoll/
    type=mixedlogit
      mixed=(normalparm=time)
      mixed=(normalparm=cv)
      mixed=(normalparm=mldum)
  nchoice=2;
  id id;
run;
proc mdc data=code.shoulder3;
  model lanechoice = time cv totaltoll/
    type=mixedlogit
      mixed=(normalparm=time)
      mixed=(normalparm=cv)
  nchoice=2;
  id id;
run;
proc mdc data=code.shoulder3;
  model lanechoice =mldum time cv/
    type=mixedlogit
      mixed=(normalparm=time)
      mixed=(normalparm=cv)
      mixed=(normalparm=mldum)
  nchoice=2;
  id id;
run;
proc mdc data=code.offpeak3;
  model lanechoice =mldum time cv totaltoll/
    type=mixedlogit
      mixed=(normalparm=time)
      mixed=(normalparm=cv)
      mixed=(normalparm=mldum)
  nchoice=2;
  id id;
run;
proc mdc data=code.offpeak3;
  model lanechoice = time cv totaltoll/
    type=mixedlogit
      mixed=(normalparm=time)
      mixed=(normalparm=cv)
  nchoice=2;
  id id;
run;
proc mdc data=code.offpeak3;
  model lanechoice =mldum time cv/
    type=mixedlogit
      mixed=(normalparm=time)
      mixed=(normalparm=cv)
      mixed=(normalparm=mldum)
  nchoice=2;
  id id;
run;
proc mdc data=code.finalmonth3;
  model lanechoice =mldum time tti totaltoll/

```

```

        type=mixedlogit
        mixed=(normalparm=time)
        mixed=(normalparm=tti)
        mixed=(normalparm=mldum)
    nchoice=2;
    id id;
run;
proc mdc data=code.finalmonth3;
    model lanechoice = time tti totaltoll/
        type=mixedlogit
        mixed=(normalparm=time)
        mixed=(normalparm=tti)
    nchoice=2;
    id id;
run;
proc mdc data=code.finalmonth3;
    model lanechoice =mldum time tti/
        type=mixedlogit
        mixed=(normalparm=time)
        mixed=(normalparm=tti)
        mixed=(normalparm=mldum)
    nchoice=2;
    id id;
run;
proc mdc data=code.peak3;
    model lanechoice =mldum time tti totaltoll/
        type=mixedlogit
        mixed=(normalparm=time)
        mixed=(normalparm=tti)
        mixed=(normalparm=mldum)
    nchoice=2;
    id id;
run;
proc mdc data=code.peak3;
    model lanechoice = time tti totaltoll/
        type=mixedlogit
        mixed=(normalparm=time)
        mixed=(normalparm=tti)
    nchoice=2;
    id id;
run;
proc mdc data=code.peak3;
    model lanechoice =mldum time tti/
        type=mixedlogit
        mixed=(normalparm=time)
        mixed=(normalparm=tti)
        mixed=(normalparm=mldum)
    nchoice=2;
    id id;
run;
proc mdc data=code.shoulder3;
    model lanechoice =mldum time tti totaltoll/
        type=mixedlogit
        mixed=(normalparm=time)

```

```

                                mixed=(normalparm=tti)
                                mixed=(normalparm=mldum)
                                nchoice=2;
                                id id;
run;
proc mdc data=code.shoulder3;
    model lanechoice = time tti totaltoll/
        type=mixedlogit
            mixed=(normalparm=time)
            mixed=(normalparm=tti)
        nchoice=2;
    id id;
run;
proc mdc data=code.shoulder3;
    model lanechoice =mldum time tti/
        type=mixedlogit
            mixed=(normalparm=time)
            mixed=(normalparm=tti)
            mixed=(normalparm=mldum)
        nchoice=2;
    id id;
run;
proc mdc data=code.offpeak3;
    model lanechoice =mldum time tti totaltoll/
        type=mixedlogit
            mixed=(normalparm=time)
            mixed=(normalparm=tti)
            mixed=(normalparm=mldum)
        nchoice=2;
    id id;
run;
proc mdc data=code.offpeak3;
    model lanechoice = time tti totaltoll/
        type=mixedlogit
            mixed=(normalparm=time)
            mixed=(normalparm=tti)
        nchoice=2;
    id id;
run;
proc mdc data=code.offpeak3;
    model lanechoice =mldum time tti/
        type=mixedlogit
            mixed=(normalparm=time)
            mixed=(normalparm=tti)
            mixed=(normalparm=mldum)
        nchoice=2;
    id id;
run;
proc mdc data=code.finalmonth3;
    model lanechoice =mldum time bti totaltoll/
        type=mixedlogit
            mixed=(normalparm=time)
            mixed=(normalparm=bti)
            mixed=(normalparm=mldum)

```

```

        nchoice=2;
    id id;
run;
proc mdc data=code.finalmonth3;
    model lanechoice = time bti totaltoll/
        type=mixedlogit
            mixed=(normalparm=time)
                mixed=(normalparm=bti)
        nchoice=2;
    id id;
run;
proc mdc data=code.finalmonth3;
    model lanechoice =mldum time bti/
        type=mixedlogit
            mixed=(normalparm=time)
                mixed=(normalparm=bti)
                    mixed=(normalparm=mldum)
        nchoice=2;
    id id;
run;
proc mdc data=code.peak3;
    model lanechoice =mldum time bti totaltoll/
        type=mixedlogit
            mixed=(normalparm=time)
                mixed=(normalparm=bti)
                    mixed=(normalparm=mldum)
        nchoice=2;
    id id;
run;
proc mdc data=code.peak3;
    model lanechoice = time bti totaltoll/
        type=mixedlogit
            mixed=(normalparm=time)
                mixed=(normalparm=bti)
        nchoice=2;
    id id;
run;
proc mdc data=code.peak3;
    model lanechoice =mldum time bti/
        type=mixedlogit
            mixed=(normalparm=time)
                mixed=(normalparm=bti)
                    mixed=(normalparm=mldum)
        nchoice=2;
    id id;
run;
proc mdc data=code.shoulder3;
    model lanechoice =mldum time bti totaltoll/
        type=mixedlogit
            mixed=(normalparm=time)
                mixed=(normalparm=bti)
                    mixed=(normalparm=mldum)
        nchoice=2;
    id id;

```

```

run;
proc mdc data=code.shoulder3;
    model lanechoice = time bti totaltoll/
        type=mixedlogit
            mixed=(normalparm=time)
                mixed=(normalparm=bti)
        nchoice=2;
    id id;
run;
proc mdc data=code.shoulder3;
    model lanechoice =mldum time bti/
        type=mixedlogit
            mixed=(normalparm=time)
                mixed=(normalparm=bti)
                    mixed=(normalparm=mldum)
        nchoice=2;
    id id;
run;
proc mdc data=code.offpeak3;
    model lanechoice =mldum time bti totaltoll/
        type=mixedlogit
            mixed=(normalparm=time)
                mixed=(normalparm=bti)
                    mixed=(normalparm=mldum)
        nchoice=2;
    id id;
run;
proc mdc data=code.offpeak3;
    model lanechoice = time bti totaltoll/
        type=mixedlogit
            mixed=(normalparm=time)
                mixed=(normalparm=bti)
        nchoice=2;
    id id;
run;
proc mdc data=code.offpeak3;
    model lanechoice =mldum time bti/
        type=mixedlogit
            mixed=(normalparm=time)
                mixed=(normalparm=bti)
                    mixed=(normalparm=mldum)
        nchoice=2;
    id id;
run;
proc mdc data=code.finalmonth3;
    model lanechoice =mldum time pti totaltoll/
        type=mixedlogit
            mixed=(normalparm=time)
                mixed=(normalparm=pti)
                    mixed=(normalparm=mldum)
        nchoice=2;
    id id;
run;
proc mdc data=code.finalmonth3;

```

```

        model lanechoice = time pti totaltoll/
            type=mixedlogit
                mixed=(normalparm=time)
                    mixed=(normalparm=pti)
            nchoice=2;
        id id;
run;
proc mdc data=code.finalmonth3;
    model lanechoice =mldum time pti/
        type=mixedlogit
            mixed=(normalparm=time)
                mixed=(normalparm=pti)
                    mixed=(normalparm=mldum)
        nchoice=2;
    id id;
run;
proc mdc data=code.peak3;
    model lanechoice =mldum time pti totaltoll/
        type=mixedlogit
            mixed=(normalparm=time)
                mixed=(normalparm=pti)
                    mixed=(normalparm=mldum)
        nchoice=2;
    id id;
run;
proc mdc data=code.peak3;
    model lanechoice = time pti totaltoll/
        type=mixedlogit
            mixed=(normalparm=time)
                mixed=(normalparm=pti)
        nchoice=2;
    id id;
run;
proc mdc data=code.peak3;
    model lanechoice =mldum time pti/
        type=mixedlogit
            mixed=(normalparm=time)
                mixed=(normalparm=pti)
                    mixed=(normalparm=mldum)
        nchoice=2;
    id id;
run;
proc mdc data=code.shoulder3;
    model lanechoice =mldum time pti totaltoll/
        type=mixedlogit
            mixed=(normalparm=time)
                mixed=(normalparm=pti)
                    mixed=(normalparm=mldum)
        nchoice=2;
    id id;
run;
proc mdc data=code.shoulder3;
    model lanechoice = time pti totaltoll/
        type=mixedlogit

```



```

                mixed=(normalparm=time)
                mixed=(normalparm=pti)
            nchoice=2;
        id id;
run;
proc mdc data=code.shoulder3;
    model lanechoice =mldum time pti/
        type=mixedlogit
            mixed=(normalparm=time)
                mixed=(normalparm=pti)
                    mixed=(normalparm=mldum)
            nchoice=2;
    id id;
run;
proc mdc data=code.offpeak3;
    model lanechoice =mldum time pti totaltoll/
        type=mixedlogit
            mixed=(normalparm=time)
                mixed=(normalparm=pti)
                    mixed=(normalparm=mldum)
            nchoice=2;
    id id;
run;
proc mdc data=code.offpeak3;
    model lanechoice = time pti totaltoll/
        type=mixedlogit
            mixed=(normalparm=time)
                mixed=(normalparm=pti)
            nchoice=2;
    id id;
run;
proc mdc data=code.offpeak3;
    model lanechoice =mldum time pti/
        type=mixedlogit
            mixed=(normalparm=time)
                mixed=(normalparm=pti)
                    mixed=(normalparm=mldum)
            nchoice=2;
    id id;
run;
proc mdc data=code.finalmonth3;
    model lanechoice =mldum time mi totaltoll/
        type=mixedlogit
            mixed=(normalparm=time)
                mixed=(normalparm=mi)
                    mixed=(normalparm=mldum)
            nchoice=2;
    id id;
run;
proc mdc data=code.finalmonth3;
    model lanechoice = time mi totaltoll/
        type=mixedlogit
            mixed=(normalparm=time)
                mixed=(normalparm=mi)

```

```

        nchoice=2;
    id id;
run;
proc mdc data=code.finalmonth3;
    model lanechoice =mldum time mi/
        type=mixedlogit
            mixed=(normalparm=time)
                mixed=(normalparm=mi)
                    mixed=(normalparm=mldum)
        nchoice=2;
    id id;
run;
proc mdc data=code.peak3;
    model lanechoice =mldum time mi totaltoll/
        type=mixedlogit
            mixed=(normalparm=time)
                mixed=(normalparm=mi)
                    mixed=(normalparm=mldum)
        nchoice=2;
    id id;
run;
proc mdc data=code.peak3;
    model lanechoice = time mi totaltoll/
        type=mixedlogit
            mixed=(normalparm=time)
                mixed=(normalparm=mi)
        nchoice=2;
    id id;
run;
proc mdc data=code.peak3;
    model lanechoice =mldum time mi/
        type=mixedlogit
            mixed=(normalparm=time)
                mixed=(normalparm=mi)
                    mixed=(normalparm=mldum)
        nchoice=2;
    id id;
run;
proc mdc data=code.shoulder3;
    model lanechoice =mldum time mi totaltoll/
        type=mixedlogit
            mixed=(normalparm=time)
                mixed=(normalparm=mi)
                    mixed=(normalparm=mldum)
        nchoice=2;
    id id;
run;
proc mdc data=code.shoulder3;
    model lanechoice = time mi totaltoll/
        type=mixedlogit
            mixed=(normalparm=time)
                mixed=(normalparm=mi)
        nchoice=2;
    id id;

```

```

run;
proc mdc data=code.shoulder3;
  model lanechoice =mldum time mi/
    type=mixedlogit
      mixed=(normalparm=time)
      mixed=(normalparm=mi)
      mixed=(normalparm=mldum)
  nchoice=2;
id id;
run;
proc mdc data=code.offpeak3;
  model lanechoice =mldum time mi totaltoll/
    type=mixedlogit
      mixed=(normalparm=time)
      mixed=(normalparm=mi)
      mixed=(normalparm=mldum)
  nchoice=2;
id id;
run;
proc mdc data=code.offpeak3;
  model lanechoice = time mi totaltoll/
    type=mixedlogit
      mixed=(normalparm=time)
      mixed=(normalparm=mi)
  nchoice=2;
id id;
run;
proc mdc data=code.offpeak3;
  model lanechoice =mldum time mi/
    type=mixedlogit
      mixed=(normalparm=time)
      mixed=(normalparm=mi)
      mixed=(normalparm=mldum)
  nchoice=2;
id id;
run;
proc mdc data=code.finalmonth3;
  model lanechoice =mldum time pt totaltoll/
    type=mixedlogit
      mixed=(normalparm=time)
      mixed=(normalparm=pt)
      mixed=(normalparm=mldum)
  nchoice=2;
id id;
run;
proc mdc data=code.finalmonth3;
  model lanechoice = time pt totaltoll/
    type=mixedlogit
      mixed=(normalparm=time)
      mixed=(normalparm=pt)
  nchoice=2;
id id;
run;
proc mdc data=code.finalmonth3;

```

```

        model lanechoice =mldum time pt/
        type=mixedlogit
            mixed=(normalparm=time)
            mixed=(normalparm=pt)
            mixed=(normalparm=mldum)
        nchoice=2;
    id id;
run;
proc mdc data=code.peak3;
    model lanechoice =mldum time pt totaltoll/
    type=mixedlogit
        mixed=(normalparm=time)
        mixed=(normalparm=pt)
        mixed=(normalparm=mldum)
    nchoice=2;
    id id;
run;
proc mdc data=code.peak3;
    model lanechoice = time pt totaltoll/
    type=mixedlogit
        mixed=(normalparm=time)
        mixed=(normalparm=pt)
    nchoice=2;
    id id;
run;
proc mdc data=code.peak3;
    model lanechoice =mldum time pt/
    type=mixedlogit
        mixed=(normalparm=time)
        mixed=(normalparm=pt)
        mixed=(normalparm=mldum)
    nchoice=2;
    id id;
run;
proc mdc data=code.shoulder3;
    model lanechoice =mldum time pt totaltoll/
    type=mixedlogit
        mixed=(normalparm=time)
        mixed=(normalparm=pt)
        mixed=(normalparm=mldum)
    nchoice=2;
    id id;
run;
proc mdc data=code.shoulder3;
    model lanechoice = time pt totaltoll/
    type=mixedlogit
        mixed=(normalparm=time)
        mixed=(normalparm=pt)
    nchoice=2;
    id id;
run;
proc mdc data=code.shoulder3;
    model lanechoice =mldum time pt/
    type=mixedlogit

```

```

        mixed=(normalparm=time)
        mixed=(normalparm=pt)
        mixed=(normalparm=mldum)
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak3;
    model lanechoice =mldum time pt totaltoll/
        type=mixedlogit
        mixed=(normalparm=time)
        mixed=(normalparm=pt)
        mixed=(normalparm=mldum)
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak3;
    model lanechoice = time pt totaltoll/
        type=mixedlogit
        mixed=(normalparm=time)
        mixed=(normalparm=pt)
    nchoice=2;
    id id;
run;
proc mdc data=code.offpeak3;
    model lanechoice =mldum time pt/
        type=mixedlogit
        mixed=(normalparm=time)
        mixed=(normalparm=pt)
        mixed=(normalparm=mldum)
    nchoice=2;
    id id;
run

```